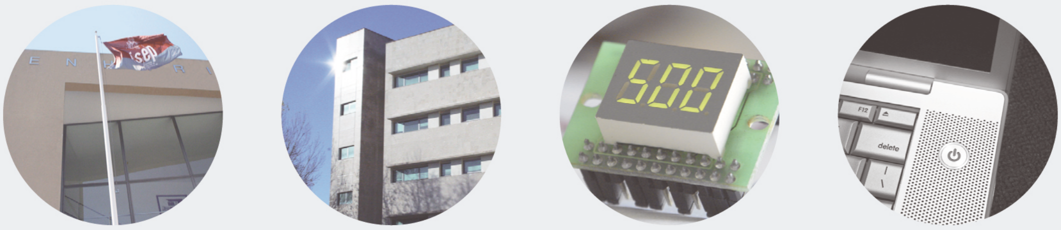
INSTITUTO SUPERIOR DE ENGENHARIA DO PORTO

MESTRADO EM ENGENHARIA ELECTROTÉCNICA - SISTEMAS ELÉCTRICOS DE ENERGIA

isep



Optimization of Aggregators Energy Resources considering Local Markets and Electric Vehicle Penetration

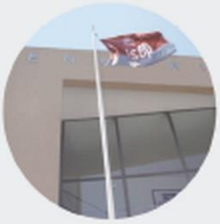
JOSÉ RAFAEL GUEDES DE ALMEIDA

novembro de 2021

POLITÉCNICO
DO PORTO

INSTITUTO SUPERIOR DE ENGENHARIA DO PORTO

MESTRADO EM ENGENHARIA ELECTROTÉCNICA - SISTEMAS ELÉCTRICOS DE ENERGIA



Optimization of Aggregators Energy Resources considering Local Markets and Electric Vehicle Penetration

JOSÉ RAFAEL GUEDES DE ALMEIDA

Outubro de 2021

POLITÉCNICO
DO PORTO

OPTIMIZATION OF AGGREGATORS ENERGY RESOURCES CONSIDERING LOCAL MARKETS AND ELECTRIC VEHICLE PENETRATION

José Rafael Guedes de Almeida

Instituto Superior de Engenharia do Porto

Departamento de Engenharia Eletrotécnica

Mestrado em Engenharia Eletrotécnica – Sistemas Elétricos de Energia

2021

Relatório elaborado para satisfação parcial dos requisitos da Unidade Curricular de DSEE - Dissertação do Mestrado em Engenharia Eletrotécnica – Sistemas Elétricos de Energia

Candidato: José Rafael Guedes de Almeida, Nº 1161588, 1161588@isep.ipp.pt

Orientação científica: Dr. João Soares, jan@isep.ipp.pt;

Coorientação científica: Dr. Bruno Canizes, bmc@isep.ipp.pt;

Coorientação científica: Dr. Ali Fotouhi, ma.fotouhi@gmail.com.

Instituto Superior de Engenharia do Porto

Departamento de Engenharia Eletrotécnica

Mestrado em Engenharia Eletrotécnica – Sistemas Elétricos de Energia

2021

“Mathematics is the music of reason” – James Joseph Sylvester

Acknowledgments

First, I would like to thank all the people that made the realization of this thesis possible. I want to thank mainly my main supervisor, Dr. João Soares, and co-supervisors, Dr. Bruno Canizes and Dr. Ali Fotouhi, for their friendship, their availability to ask questions and clarify doubts, and for all the conditions given to make me feel at ease.

I want to thank GECAD (Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development) for the conditions given that benefited the realization of this work, the institution of ISEP that throughout these years was a place of great joys that provided me with incredible achievements on a personal and professional level.

I want to thank my friends at GECAD, Rúben Barreto, Calvin Gonçalves, and Inês Tavares for their help, knowledge, and company during this thesis.

Most importantly, I would like to thank my parents and sister, Maria de Lurdes Almeida, António Almeida, and Mariana Almeida, for their support, affection, and constant patience throughout these years.

Finally, I would like to thank all my closest friends and family for everything they gave me.

Thank you!

Resumo

O sector elétrico tem vindo a evoluir ao longo do tempo. Esta situação deve-se ao facto de surgirem novas metodologias para lidarem com a elevada penetração dos recursos energéticos distribuídos (RED), principalmente veículos elétricos (VEs). Neste caso, a gestão dos recursos energéticos tornou-se mais proeminente devido aos avanços tecnológicos que estão a ocorrer, principalmente no contexto das redes inteligentes. Este facto torna-se importante, devido à incerteza decorrente deste tipo de recursos. Para resolver problemas que envolvem variabilidade, os métodos baseados na inteligência computacional estão a se tornar os mais adequados devido à sua fácil implementação e baixo esforço computacional, mais precisamente para o caso tratado na tese, algoritmos de computação evolucionária (CE). Este tipo de algoritmo tenta imitar o comportamento observado na natureza. Ao contrário dos métodos determinísticos, a CEé tolerante à incerteza; ou seja, é adequado para resolver problemas relacionados com os sistemas energéticos. Estes sistemas são geralmente de grandes dimensões, com um número crescente de variáveis e restrições. Aqui a IC permite obter uma solução quase ótima em tempo computacional aceitável com baixos requisitos de memória. O principal objetivo deste trabalho foi propor um modelo para a programação dos recursos energéticos dos recursos dedicados para o contexto intradiário, para a hora seguinte, partindo inicialmente da programação feita para o dia seguinte, ou seja, 24 horas para o dia seguinte. Esta programação é feita por cada agregador (no total cinco) através de meta-heurísticas, com o objetivo de minimizar os custos ou maximizar os lucros. Estes agregadores estão inseridos numa cidade inteligente com uma rede de distribuição de 13 barramentos com elevada penetração de RED, principalmente energia renovável e VEs (2000 VEs são considerados nas simulações). Para modelar a incerteza associada ao RED e aos preços de mercado, vários cenários são gerados através da simulação de Monte Carlo usando as funções de distribuição de probabilidade de erros de previsão, neste caso a função de distribuição normal para o dia seguinte. No que toca à incerteza no modelo para a hora seguinte, múltiplos cenários são gerados a partir do cenário com maior probabilidade do dia seguinte. Neste trabalho, os mercados locais de eletricidade são também utilizados como estratégia para satisfazer a equação do balanço energético onde os agregadores vão para vender o excesso de energia ou comprar para satisfazer o consumo. Múltiplas meta-heurísticas de última geração são usadas para fazer este escalonamento, nomeadamente *Differential Evolution* (DE), *Hybrid-Adaptive DE with Decay function* (HyDE-DF), *DE with Estimation of Distribution Algorithm* (DEEDA), *Cellular Univariate Marginal Distribution Algorithm with Normal-Cauchy Distribution* (CUMDANCauchy++), *Hill Climbing to Ring Cellular Encode-Decode UMDA* (HC2RCEDUMDA). Os resultados mostram que o modelo proposto é eficaz para os múltiplos agregadores com variações de custo na sua maioria abaixo dos 5% em relação ao dia seguinte, exceto para o agregador e de VEs. É também aplicado um teste Wilcoxon para comparar o desempenho do algoritmo CUMDANCauchy++ com as restantes meta-heurísticas. O CUMDANCauchy++ mostra resultados competitivos tendo melhor performance que todos os algoritmos para todos os agregadores exceto o DEEDA que apresenta resultados semelhantes. Uma estratégia de aversão ao risco é implementada para um agregador no contexto do dia seguinte para se obter uma solução mais segura e robusta. Os resultados mostram um aumento de quase 4% no investimento, mas uma redução de até 14% para o custo dos piores cenários.

Palavras-Chave

Agregadores, aversão ao risco, gestão de recursos energéticos, inteligência computacional, rede inteligente, veículos elétricos

Abstract

The electrical sector has been evolving. This situation is because new methodologies emerge to deal with the high penetration of distributed energy resources (DER), mainly electric vehicles (EVs). In this case, energy resource management has become increasingly prominent due to the technological advances that are taking place, mainly in the context of smart grids. This factor becomes essential due to the uncertainty of this type of resource. To solve problems involving variability, methods based on computational intelligence (CI) are becoming the most suitable because of their easy implementation and low computational effort, more precisely for the case treated in this thesis, evolutionary computation (EC) algorithms. This type of algorithm tries to mimic behavior observed in nature. Unlike deterministic methods, the EC is tolerant of uncertainty, and thus it is suitable for solving problems related to energy systems. These systems are usually of high dimensions, with an increased number of variables and restrictions. Here the CI allows obtaining a near-optimal solution in good computational time with low memory requirements. This work's main objective is to propose a model for the energy resource scheduling of the dedicated resources for the intraday context, for the our-ahead, starting initially from the scheduling done for the day ahead, that is, 24 hours for the next day. This scheduling is done by each aggregator (in total five) through metaheuristics to minimize the costs or maximize the profits. These aggregators are inserted in a smart city with a distribution network of 13 buses with a high penetration of DER, mainly renewable energy and EVs (2000 EVs are considered in the simulations). Several scenarios are generated through Monte Carlo Simulation using the forecast errors' probability distribution functions, the normal distribution function for the day-ahead to model the uncertainty associated with DER and market prices. Multiple scenarios are developed through the highest probability scenario from the day-ahead when it comes to intraday uncertainty. In this work, local electricity markets are used as a mechanism to satisfy the energy balance equation where each aggregator can sell the excess of energy or buy more to meet the demand. Several recent and modern metaheuristics are used to solve the proposed problems in the thesis, namely Differential Evolution (DE), Hybrid-Adaptive DE with Decay function (HyDE-DF), DE with Estimation of Distribution

Algorithm (DEEDA), Cellular Univariate Marginal Distribution Algorithm with Normal-Cauchy Distribution (CUMDANCauchy++), Hill Climbing to Ring Cellular Encode-Decode UMDA (HC2RCEDUMDA). Results show that the proposed model is effective for the multiple aggregators. The metaheuristics present satisfactory results and mostly less than 5% variation in costs from the day-ahead except for the EV aggregator. A Wilcoxon test is also applied to compare the performance of the CUMDANCauchy++ algorithm with the remaining metaheuristics. CUMDANCauchy++ shows competitive results beating all algorithms in all aggregators except for DEEDA, which presents similar results. A risk aversion strategy is implemented for an aggregator in the day-ahead context to get a safer and more robust solution. Results show an increase of nearly 4% in day-ahead cost but a reduction of up to 14% of worst scenario cost.

Keywords

Aggregators, computational intelligence, electric vehicles, energy resource management, risk-aversion, smart grid

Index

ACKNOWLEDGMENTS .... **I**

RESUMO .... **III**

ABSTRACT .... **V**

INDEX .... **VII**

INDEX OF FIGURES .... **IX**

INDEX OF TABLES .... **XIII**

ACRONYMS .... **XV**

1. INTRODUCTION **1**

1.1. MOTIVATION 2
1.2. OBJECTIVES 3
1.3. SCHEDULE 3
1.4. PUBLICATIONS 4
1.5. DOCUMENT ORGANIZATION 6

2. THEORETICAL BACKGROUND **7**

2.1. COMPUTATIONAL INTELLIGENCE 7
2.1.1. Differential evolution 8
2.1.2. Hybrid-adaptative differential evolution with decay function 10
2.1.3. Differential evolution with estimation of distribution algorithm 11
2.1.4. Cellular univariate marginal distribution algorithm 12
2.1.5. Hill climbing to ring cellular encode-decode umda 13
2.2. SMART GRID 14
2.3. ELECTRIC VEHICLES 15
2.4. ENERGY RESOURCE MANAGEMENT 17
2.5. DEMAND RESPONSE AND ELECTRIC VEHICLE FLEXIBILITY 20
2.5.1. Smart charging 21
2.5.2. Vehicle-to-grid 22
2.6. LOCAL ELECTRICITY MARKETS 23
2.7. VALUE-AT-RISK 27
2.8. CHAPTER CONCLUSIONS 28

3. METHODOLOGY **31**

3.1. ENERGY RESOURCE SCHEDULING FORMULATION 31
3.2. RISK-BASED ERM 39
3.2.1. Risk-neutral formulation 39
3.2.2. Risk-averse formulation 40
3.3. OPTIMIZATION TECHNIQUE 41
3.3.1. Program structure 42
3.3.2. Encoding of individuals 43
3.3.3. Fitness function 45
3.4. UNCERTAINTY 47
3.5. CHAPTER CONCLUSIONS 50

4. CASE STUDY 51

4.1. DISTRIBUTION NETWORK AND EV SCENARIO SIMULATOR 51
4.2. ENERGY RESOURCE INFORMATION 55
4.3. RISK-BASED ENERGY RESOURCE INFORMATION 59
4.4. ALGORITHM PARAMETERS 61
4.5. CHAPTER CONCLUSIONS 62

5. RESULTS AND DISCUSSION 63

5.1. DAY-AHEAD AND INTRADAY SCHEDULING RESULTS 63
5.2. ALGORITHM PERFORMANCE 72
5.3. RISK-BASED STRATEGY RESULTS 75
5.4. CHAPTER CONCLUSIONS 79

6. CONCLUSIONS 81

6.1. FINAL CONCLUSIONS 81
6.2. FUTURE WORK 82

REFERENCES 85

Index of Figures

Figure 1 Expected project scheduling. 4

Figure 2 Standard DE algorithm. 9

Figure 3 Decay factor is used to gradually switch between the original HyDE operator to the DE/rand/1 operator. 11

Figure 4 Structure of the DEEDA optimization algorithm. 12

Figure 5 Flowchart of the CUMDANCauchy++ algorithm. 13

Figure 6 Number of electric cars in the major regions, 2010-20. 16

Figure 7 EV services provided for different parties in power systems. 17

Figure 8 Structure of the proposed energy management for a network of microgrids. 19

Figure 9 Typical data flow for a smart charging service. 22

Figure 10 Example of a V2G system. 23

Figure 11 Electricity tradings in liberalised electricity markets. 24

Figure 12 Market framework with local and central electricity and ancillary service market. 25

Figure 13 Wholesale and local market modulation. 26

Figure 14 Day-ahead ERM model. 32

Figure 15 Hour-ahead ERM model. 37

Figure 16 Graphical representation of VaR, CVaR and Z_{Ex} through normal and cumulative distribution functions. 40

Figure 17 Flowchart of the main function of the proposed optimization technique. 42

Figure 18 Representation of the generated solution for the intraday ERM model. 44

Figure 19 Fitness function structure of ERM model. 45

Figure 20 Fitness function of the risk-based optimization. 46

Figure 21 Scenario tree. 48

Figure 22 Smart city schematic. 52

Figure 23 Single-line diagram of the distribution network. 52

Figure 24 Average forecast error for generation technologies. 55

Figure 25 Total demand and renewable generation forecast for each aggregator in the intraday time horizon. 57

Figure 26 External supplier, WS market, and LEM prices for the intraday time horizon. 58

Figure 27 Load demand, and non-dispatchable generation for risk-based model. 60

Figure 28 External supplier, and WS market prices for risk-based model. 60

Figure 29 Day-ahead scheduling results for aggregator 1 regarding power a) generation; b) consumption. 64

Figure 30 Day-ahead scheduling results for aggregator 2 regarding power a) generation; b) consumption. 65

Figure 31 Day-ahead scheduling results for aggregator 3 regarding power a) generation; b) consumption. 66

Figure 32 Day-ahead scheduling results for aggregator 4 regarding power a) generation; b) consumption. 66

Figure 33 Day-ahead scheduling results for aggregator 5 regarding power a) generation; b) consumption. 67

Figure 34 A comparison of the day-ahead total costs with the overall intraday costs generated by each EA. 69

Figure 35 Hour-ahead scheduling results for aggregator 1 regarding power a) generation; b) consumption. 70

Figure 36 Hour-ahead scheduling results for aggregator 2 regarding power a) generation; b) consumption. 70

Figure 37 Hour-ahead scheduling results for aggregator 3 regarding power a) generation; b) consumption. 71

Figure 38 Hour-ahead scheduling results for aggregator 4 regarding power a) generation; b) consumption. 72

Figure 39 Hour-ahead scheduling results for aggregator 5 regarding power a) generation; b) consumption. 72

Figure 40 A comparison of the day-ahead overall costs with the overall intraday costs generated by each tested metaheuristic. 75

Figure 41 Day-ahead scheduling results for the risk-neutral strategy regarding power a) generation; b) consumption. 77

Figure 42 Day-ahead scheduling results for the risk-averse strategy regarding power a) generation; b) consumption. 77

Figure 43 Total scenario cost for risk-neutral and risk-averse approaches. 78

Index of Tables

Table 1 Metaheuristics used to solve energy problems. 8

Table 2 Traditional electric grid versus the smart grid. 15

Table 3 Dimension of each individual for each aggregator in the day-ahead ERM. 45

Table 4 Dimension of each individual for each aggregator in the intraday ERM. 45

Table 5 Inputs for the Electric vehicle Trip Simulator. 53

Table 6 Electric vehicle model description. 54

Table 7 Electric vehicle model characteristics. 54

Table 8 EV classes distribution. 55

Table 9 Energy resources information of each aggregator in the day-ahead model. 56

Table 10 Energy resources information of each aggregator in the intraday model. 59

Table 11 EAs parameters. 62

Table 12 Day-ahead objective function results and optimization time. 64

Table 13 Intraday cost results, variation, penalties, and optimization time by the tested EAs. 68

Table 14 Overall intraday results and optimization time by the tested EAs over 20 runs. 73

Table 15 Results from the Wilcoxon signed-rank test. 74

Table 16 Cost components in the proposed strategies. 76

Acronyms

AI	–	Artificial intelligence
ANN	–	Artificial Neural Network
CEM	–	Central Electricity Market
CHP	–	Combined Heat and Power
CI	–	Computational intelligence
CUMDANCauchy	–	Cellular Univariate Marginal Distribution Algorithm
CVaR	–	Conditional Value-at-Risk
DR	–	Demand Response
DE	–	Differential Evolution
DEEDA	–	Differential Evolution with Estimation of Distribution Algorithm
DER	–	Distributed Energy Resources
DG	–	Distributed Generation
DN	–	Distribution Network
DSO	–	Distribution System Operator
EA	–	Evolutionary Algorithm
ENS	–	Energy not supplied
ERM	–	Energy Resource Management
EV	–	Electric Vehicle

ESS	–	Energy Storage System
GA	–	Genetic Algorithm
HC2RCEDUMDA	–	Hill Climbing to Ring Cellular Encode-Decode Univariate Marginal Distribution Algorithm
HS	–	Harmony Search
HyDE-DF	–	Hybrid-Adaptive Differential Evolution with Decay Function
HDSA	–	Hybrid Dynamic Search Algorithm
HOA	–	Hybrid Optimization Algorithm
ICT	–	Information and Communication Technologies
LEM	–	Local Electricity Market
LEP	–	Local Energy Provider
LM	–	Local Market
MOPSO	–	Multi-objective Particle Swarm Optimization
NSGA-II	–	Non-dominated Sorting Genetic Algorithm II
OF	–	Objective function
PSO	–	Particle Swarm Optimization
SG	–	Smart Grid
SoC	–	State-of-Charge
TSO	–	Transmission System Operator
VaR	–	Value-at-Risk
W-PSO	–	Weighted Particle Swarm Optimization

WS	–	Wholesale

1. INTRODUCTION

The work carried out to elaborate this document was done in collaboration with the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) within the CENERGETIC project[1]. The CENERGETIC project: Coordinated ENErgy Resource manaGEment under uncerTainty considering electrIc vehiCles and demand flexibility in distribution networks, aims to address a relevant societal problem by improving the integration of renewable energy resources and electric vehicles (EVs) in smart grids (SGs). This research has received funding from FEDER funds through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020), under Project POCI-01-0145-FEDER-028983; by National Funds through the FCT Portuguese Foundation for Science and Technology, under Projects PTDC/EEI-EEE/28983/2017(CENERGETIC), UIDB/000760/2020, and UIDP/00760/2020.

This chapter presents an introduction to the work with the motivation that led to the proposal and development of the topic, the main objectives to be taken into consideration, an expected timeframe for the project fulfillment and the document organization.

[1] http://www.gecad.isep.ipp.pt/CENERGETIC

1.1. MOTIVATION

In the future distribution network (DN), several electricity suppliers and/or energy aggregators[2] will coexist in a highly competitive environment. This situation occurs because power systems are moving from structures integrated vertically to deregulated markets with the increasing appearance of new actors [1]. Each supplier, and aggregators' objective is to offer the best energy product to their customers at the best price to obtain the highest return [2]. These aggregators can establish contracts with apartments, residential buildings, services, industry, and EVs either for their consumption or for their production (prosumers[3]) [3], [4].

According to each aggregator's resources, they will seek to minimize their costs or maximize their profits. As such, each one will have to make optimal management of these resources. This management is always subject to uncertainty, which increases the further it is from real-time; still, long-term and mid-term planning is necessary and should not be avoided. The intention is to make this management as close as possible to real-time to mitigate deviations in forecasts and the underlying uncertainty. Still, the time for decision-making is shortened. So day-ahead management should still be made. It is essential because there is more time for the aggregators to decide, and the day-ahead scheduling will complement the intraday scheduling.After this management, aggregators should submit their scheduling for approval of the network in which they are operating through the distribution system operator (DSO) so that there are no problems for the DN [5].

In order to provide the decision-maker with an enhanced energy resource management (ERM) tool, a risk-based mechanism is implemented in this thesis to provide a more robust solution in case of extreme events (hedging risk), such as a spike in market prices, a reduction in renewables availability, and other events that despite the very low probability of occurrence, their realization may result in undesirable effects and hinder the effectiveness of

[2] Entity that bundles distributed energy resources (a virtual power plant) for market participation

[3] Entity that is both a consumer and energy producer

traditional ERM tools. This aspect is novel in the current state of the art, where risk-based analysis has mostly been applied to energy planning problems [6], [7].

1.2. OBJECTIVES

This thesis's main objective is to optimize aggregators' energy resources in a competitive environment considering local transactions and intensive penetration of EVs. As such, work was managed by objectives:

- Development of advanced scheduling algorithms considering the various contracts that aggregators can establish;
- Algorithms based on heuristics to respond to the complexities of the problem and time to solve the problem;
- Consider different scheduling phases in the day-ahead and intraday and/or near real-time horizon;
- Consideration of uncertainty in the various horizon phases and high penetration of renewables and EVs;
- Implementation of risk analysis methodology in the day-ahead scheduling of energy resources, known as VaR (value-at-risk) and CVaR (conditional value-at-risk).

1.3. SCHEDULE

The schedule of this dissertation work is presented in Figure 1. This schedule included tasks such as the study of literature corresponding to the theme of this work, the writing of the knowledge obtained from this study, which corresponds to the writing of this document. Then the project's development proceeded with the modulation of optimization algorithms, the creation of scenarios for resource uncertainty, and the ERM of each aggregator for different time horizons with the integration of local electricity markets (LEMs). A risk-based strategy was applied to an aggregator for the day-ahead optimization. Finally, the results were carefully analyzed, with the final writing of the dissertation.

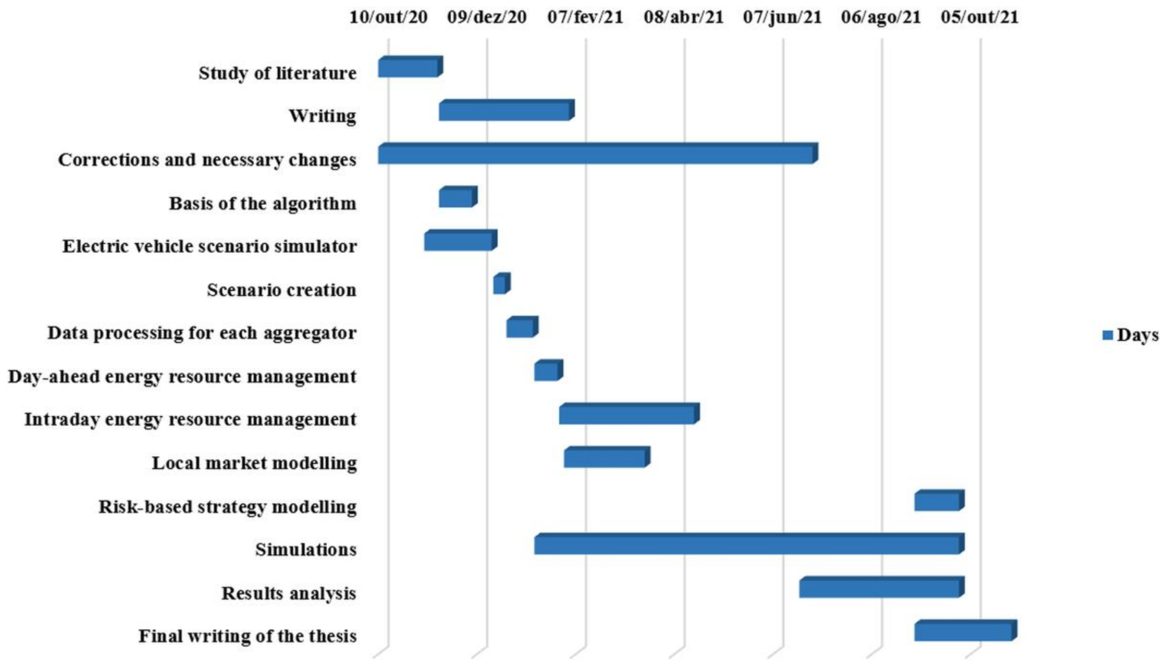


Figure 1 Expected project scheduling.

1.4. PUBLICATIONS

The work already done for this dissertation resulted in multiple scientific papers. The first three articles have already been accepted and published. The following are accepted for presentation, with the final two already being presented, just awaiting publication. The papers are:

Book Chapter

- J. Almeida, and J. Soares, "Chapter 2 - Integration of electric vehicles in local energy markets," in Local Electricity Markets, pp. 21–36, 2021, doi: 10.1016/B978-0-12-820074-2.00018-6.

Journal Papers

- J. Almeida, J. Soares, B. Canizes, and Z. Vale, "Coordination strategies in distribution network considering multiple aggregators and high penetration of electric vehicles," Procedia Computer Science, vol. 186, pp. 698–705, 2021, doi: 10.1016/j.procs.2021.04.192.

- B. Canizes, J. Soares, J. Almeida, and Z. Vale, “Hour-ahead Energy Resource Scheduling Optimization for Smart Power Distribution Networks considering Local Energy Market,” in Energy Reports, vol. xx, pp. xx, presented at 8th International Conference on Energy and Environment Research (ICEER 2021).

- J. Soares, J. Almeida, L. Gomes, B. Canizes, and Z. Vale, E. A. Neto, “Electric vehicles local flexibility strategies for congestion relief on distribution networks,” in Energy Reports, vol. xx, pp. xx, presented at 8th International Conference on Energy and Environment Research (ICEER 2021).

Conference Papers

- J. Almeida, J. Soares, B. Canizes, F. Lezama, M. A. Ghazvini Fotouhi, and Z. Vale, “Evolutionary Algorithms for Energy Scheduling under uncertainty considering Multiple Aggregators,” in 2021 IEEE Congress on Evolutionary Computation (CEC), Kraków, Poland, Jun. 2021, pp. 225–232. doi: 10.1109/CEC45853.2021.9504942.

- J. Almeida, J. Soares, B. Canizes, I. Razo-Zapata, and Z. Vale, “Intraday Energy Resource Scheduling for Load Aggregators Considering Local Market,” in 16th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2021), Cham, 2022, pp. 233–242. doi: 10.1007/978-3-030-87869-6_22.

- J. Almeida, J. Soares, B. Canizes, F. Lezama, and Z. Vale, “Hour-ahead Energy Resource Management for EV Aggregator Analysing Local Market Impact,” in 2021 IEEE PES Innovative Smart Grid Technology, Brisbane, Australia, Dec. 2021. (accepted)

- J. Almeida, J. Soares, F. Lezama, B. Canizes, and Z. Vale, “Evolutionary Algorithms applied to the Intraday Energy Resource Scheduling in the Context of Multiple Aggregators,” in IEEE Symposium Series on Computational Intelligence (IEEE SSCI 2021), Orlando, Florida, USA, Dec. 2021. (accepted)

- B. Canizes, J. Soares, J. Almeida, W. Paris, and Zita Vale, “Energy Resource Scheduling Optimization for Smart Power Distribution Grids – Hour-ahead Horizon,” in IEEE PES Innovative Smart Grid Technologies Europe, 18-21 October 2021, pp. 1-6., Esppo, Finland.

Currently, an IEEE Access paper based on the risk methodology here shown is being written and expected to be submitted before this thesis presentation. The paper is currently titled “Risk-Based Optimal Energy Resource Scheduling considering High Penetration of Distributed Energy Resources.”

1.5. DOCUMENT ORGANIZATION

The structure of this document is as follows: In chapter 1, the main objectives and motivations are presented to accomplish this work. The following chapter presents a theoretical background detailing the various themes associated with the proposed work. Themes such as evolutionary optimization algorithms, the SG concept, the EVs, the demand response (DR) programs, the flexibility that the EVs provide are detailed, LEM, and the risk measuring tools are also described with the main conclusions drawn from the literature research being presented. The mathematical formulations of the day-ahead and intraday problems are presented in chapter 3, the optimization technique applied to the problem, and the uncertainty associated with the energy resources regarding the intraday and day-ahead time horizons with the risk-based strategy formulation for the ERM problem in the day-ahead. In chapter 4, the case study for this work starts with the description of the DN and aggregators. The parameters for the EV scenario simulator tool are also offered, and energy resources for each aggregator considering the intraday model and risk-based methodology for one aggregator in the day-ahead are also described. Finally, the multiple results obtained for the proposed simulations are given in the following section, and the main conclusions to this work are presented in chapter 6.

2. THEORETICAL BACKGROUND

This chapter presents the state of art regarding the topics of the proposed work. It presents the related work developed in the various themes shown throughout this chapter.

2.1. COMPUTATIONAL INTELLIGENCE

Algorithms based on computational intelligence (CI), in this case, evolutionary algorithms (EAs), originate from the biological evolution observed in nature through reproduction, recombination, mutation, and selection. They are defined as population-based metaheuristics. Unlike more traditional algorithms based on deterministic methods, EAs are based on stochastic processes, which means they are more tolerant to uncertainty. That is, it is suitable for solving problems related to energy systems because electrical energy systems are large systems with many variables and constraints. Here evolutionary computational (EC) based algorithms are more adequate to solve these systems' problems concerning exact optimization methods. The exact techniques, although they guarantee an optimal solution to the optimization problem, are of complex implementation and do not always generate an optimal solution in useful time. On the other hand, EAs are used to solve problems that cannot be easily solved in polynomial time, such as classically NP-hard (verifiable in polynomial time if NP-hard problem is NP-complete, where an NP problem means that the decision can be verified in polynomial time) problems allowing to obtain an optimal or near-optimal solution in useful time with low memory requirements. Examples of CI algorithms are genetic algorithm (GA) [8], non-dominated sorting GA II (NSGA-II) [9], differential evolution (DE) [10], particle swarm optimization (PSO) [11], and its variations like quantum-behaved PSO (QPSO) [12], multi-objective PSO (MOPSO) [13], weighted PSO (W-PSO) [14]. Harmony search (HS) [15], differential search algorithm (DSA) [16], hybrid DSA (HDSA) [17], hybrid optimization algorithm (HOA) [18], among several others, were researched for this work. Table 1 shows the implementation of these metaheuristics to solve optimization problems in electrical energy systems.

Evolutionary algorithms are used to optimize the ERM problem in this work because in [19], a similar situation is proposed. In the proposed competition, EAs scored better on the proposed ERM problem than other CI algorithms.

Table 1 Metaheuristics used to solve energy problems.

Reference	Metaheuristics	Optimization problem
[20]	PSO	Energy resource scheduling with EVs and DR programs in the day-ahead context.
[21]	DE, PSO, QPSO, DSA	Large-Scale Energy Resource Management in SGs.
[18]	Tabu Search, GRASP, HOA	Plug-in EV charging coordination.
[22]	W-PSO, MOPSO, NSGA-II	Energy resource management in SG with multi-objective goals.
[17]	PSO, QPSO, DSA, HDSA	Large-Scale Energy Resource Management in SGs.

2.1.1. Differential evolution

Storn and Price first introduced the DE algorithm in 1995 [10]. DE optimizes a problem through the combination of existing solutions and new solutions created by it. This algorithm keeps the solutions that best fit the problem in question or present better fitness. This algorithm's steps are: first, a solution is generated (target vector), then through mutation, a donor vector is generated and through recombination, a trial vector is generated like Figure 2 shows.

In this algorithm, the selection of better solutions is performed through greedy selection between the target and trial vectors only after the generation of all trial vectors. The donor vector in its simplest form can be represented as:

$$V = X_{r1} + F\,(X_{r2} - X_{r3}). \tag{1}$$

Where V represents the donor vector, X_{r1}, X_{r2}, X_{r3} are three random solutions from the population that are different from each one. F is a scaling factor of constant value comprehended between 0 and 1.

This algorithm presents several mutation strategies which in general can be represented as "*DE/x/y/z*", where x represents the vector to be mutated, y is the number of difference vectors (random solutions) required for mutation, and z is the type of crossover mechanism to be used (exponential or binomial). Figure 2 presents the process performed in the standard DE algorithm with the "*DE/rand/1*" mutation strategy.

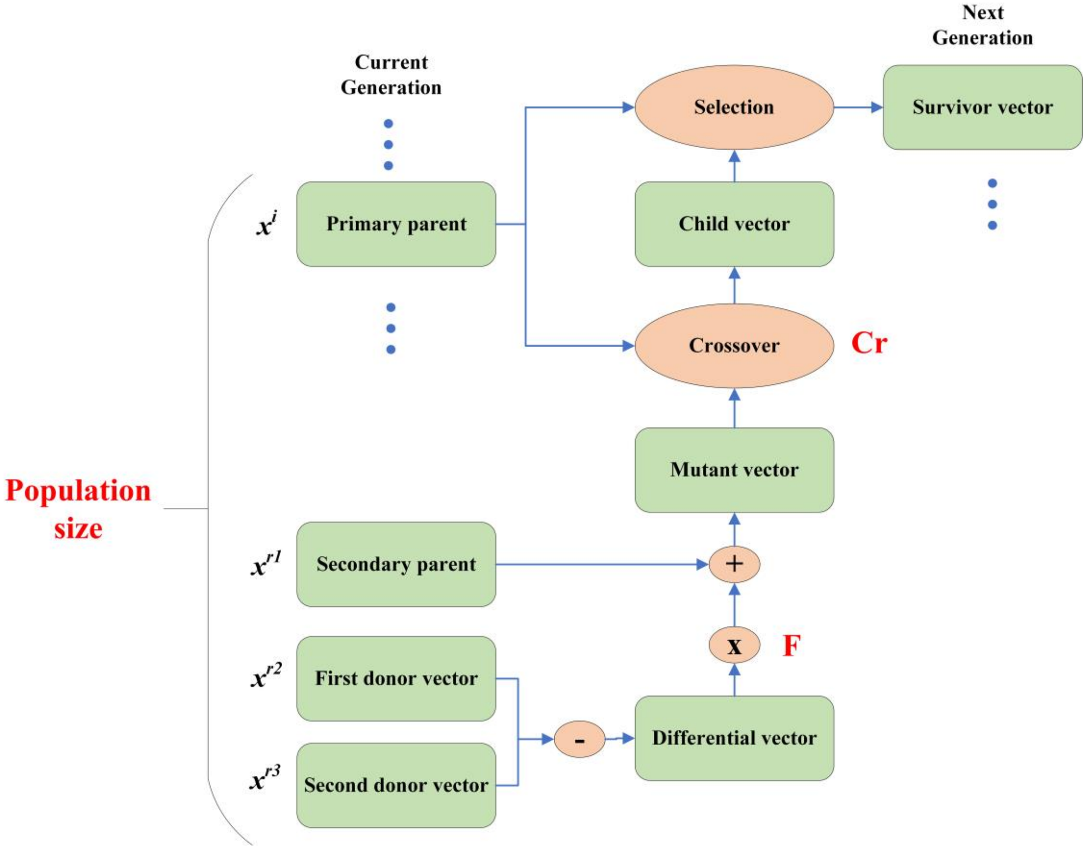


Figure 2 Standard DE algorithm.

New optimization applications in electrical power systems have emerged based on DE. The work in [21] analyzes the use of DE in a 33 bus DN with high penetration of distributed energy resources (DER) and DR programs. The authors analyze the performance of the algorithm with four state-of-the-art mutation strategies. A comparison between these strategies, other EAs and a deterministic method, is made with over 50 runs of the algorithms. In [23] an optimal active-reactive power dispatch using an efficient DE algorithm is presented. This algorithm uses an arithmetic recombination crossover and adapts its scaling factor based on the Laplace distribution providing excellent solutions.

2.1.2. HYBRID-ADAPTATIVE DIFFERENTIAL EVOLUTION WITH DECAY FUNCTION

Hybrid-Adaptive Differential Evolution with Decay Function (HyDE-DF) [24] is a state-of-the-art metaheuristic based on DE that uses the mutation operator "*DE/target-to-perturbed_best/1*", the same as the normal hybrid-adaptative DE with a decay factor δ_G. This factor decreases gradually according to the number of iterations. The mutation operator of the HyDE-DF algorithm is calculated as follows:

$$\vec{m} = \vec{x}_{i,G} + \delta_G \cdot [F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})] + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}). \quad (2)$$

Where $\vec{x}_{r1,G}$, $\vec{x}_{r2,G}$ are different from $\vec{x}_{i,G}$, the current target vector, and $\vec{x}_{best}$ is the best solution found. F_i^1, and F_i^2 are two scale factors within the range [0,1] independent for each individual i, where $\epsilon = N(F_i^3, 1)$ which represents a random perturbation factor, from normal distribution with mean value of F_i^3, and standard deviation 1. F_i^1, F_i^2, and F_i^3, are updated each iteration following the self-adaptive parameter mechanism of jDE algorithm [25]. δ_G is necessary to decrease the influence of the term $F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})]$ responsible for the fast convergence to the best individual in the population. In an initial phase, the algorithm presents a greater diversity. It is said that there is a greater exploitation following the best solution. Small adjustments are made in the decay function in the final phases so that smaller jumps are made in the research space, and there is greater local exploration like Figure 3 shows [26].

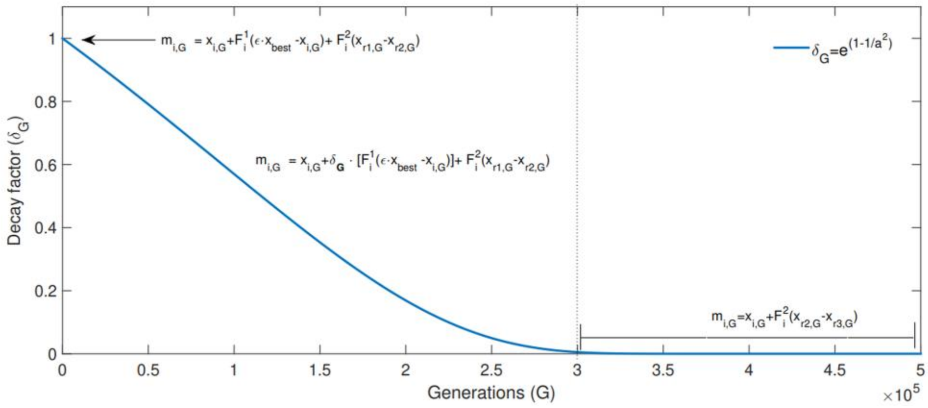


Figure 3 Decay factor is used to gradually switch between the original HyDE operator to the DE/rand/1 operator [26].

Reference [27] uses HyDE-DF algorithm as well as many other EAs to find the optimal bidding of multiple agents in a competitive environment considering local transactions. It can be concluded from this work that the existence of local markets (LMs) increases the agents' incomes (or lowers the agents' costs).

2.1.3. DIFFERENTIAL EVOLUTION WITH ESTIMATION OF DISTRIBUTION ALGORITHM

The DE with Estimation of Distribution Algorithm (DEEDA) [28] is an EA that in an initial phase uses the standard DE algorithm to obtain a partial solution using in this case the "*DE/rand/bin*" mutation factor. The DE runs through a certain number of iterations given by a step parameter defined by the user. The best solution found by the DE algorithm is then passed as an argument to the EDA. In the EDA a population and a subpopulation are created through selection of individuals. After Normal and Cauchy distributions are used to generate a new population based on the selected individuals in the subpopulation, and the global solution is found through selection like Figure 4 shows. Combining these two different algorithms helps the optimum solution to be guided on a correct global scale. This algorithm was used in the *"2020 Competition on Evolutionary Computation in the Energy Domain: Smart Grid Applications"* obtaining great results placing in the higher rankings of the competition [19].

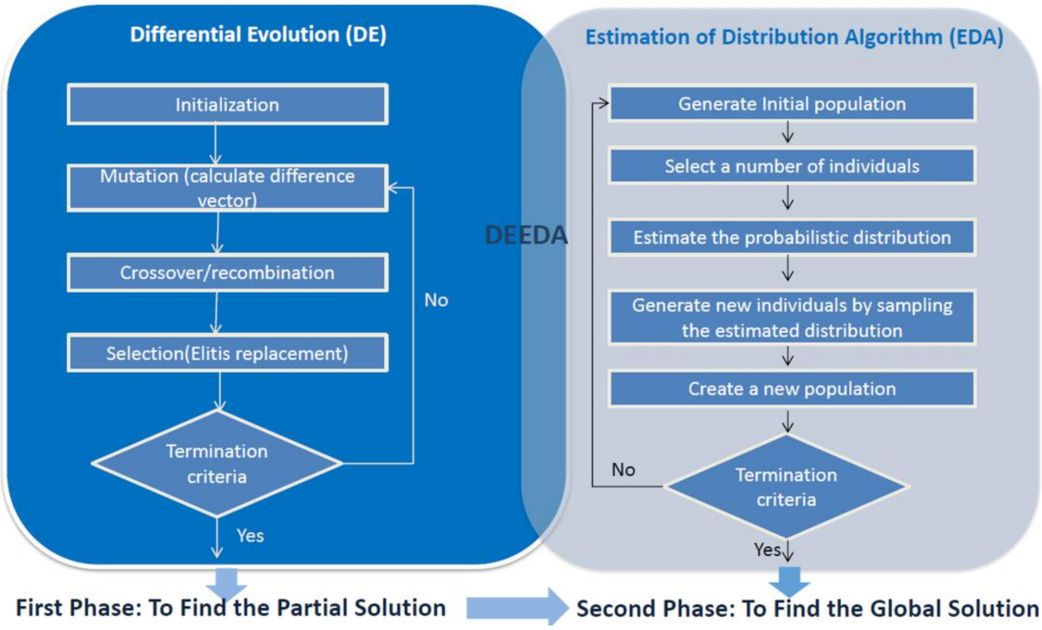


Figure 4 Structure of the DEEDA optimization algorithm [28].

2.1.4. CELLULAR UNIVARIATE MARGINAL DISTRIBUTION ALGORITHM

Cellular Univariate Marginal Distribution Algorithm (CUMDANCauchy) [29] is a cellular EA that uses the Normal and Cauchy distributions to develop a new solution. To handle the uncertainty associated with DN resources, CUMDANCauchy++ is an upgrade to the prior technique. This algorithm initially generates a random solution randomly between the problem variable bounds. A number of parent solutions are also selected from the initial population generated where a learning process consisting of the estimation of the Normal and Cauchy distributions applied to the parent solutions which creates a new population. After a selection of individuals is made and the solution is updated consisting in a mechanism of comparison of s_{best} and $global_{best}$, that is, if the fitness of x individuals is less than the fitness of this $global_{best}$, this parameter is then updated with the best value found in the fitness of these individuals. The described process of the optimization algorithm can be seen in Figure 5.

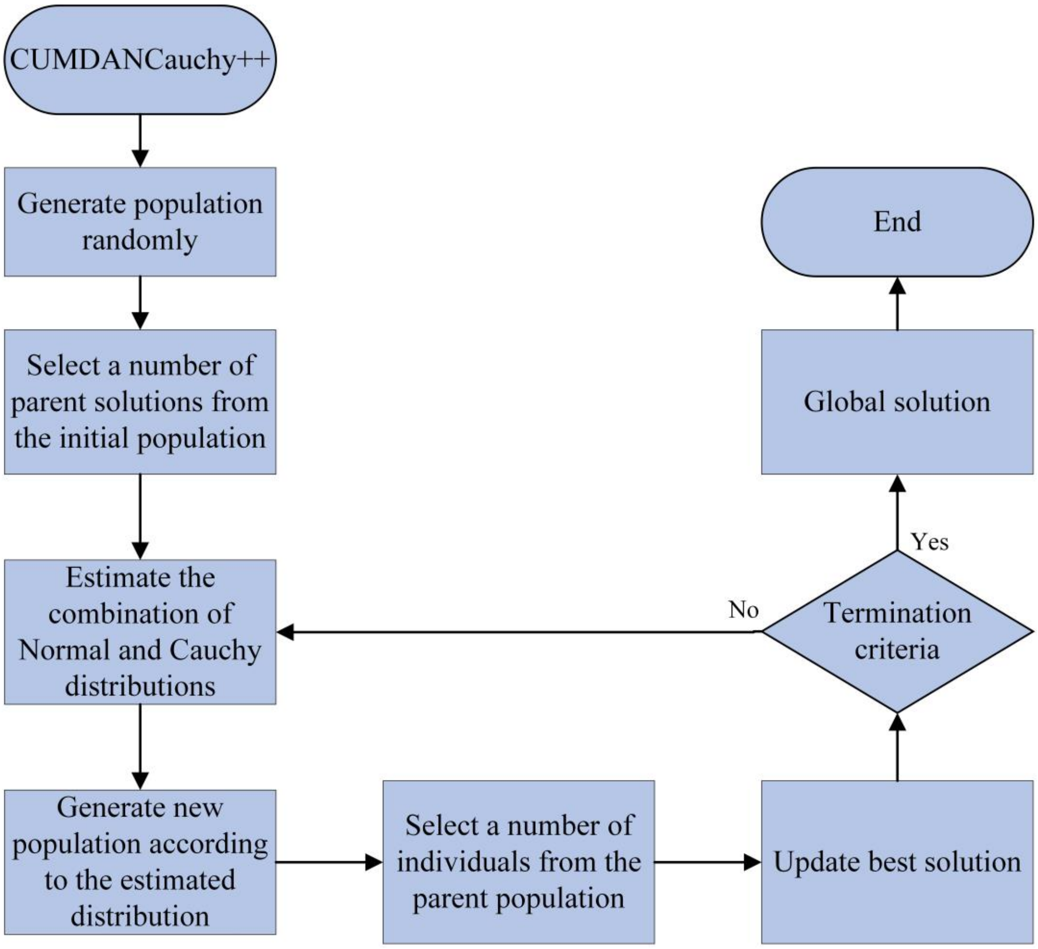


Figure 5 Flowchart of the CUMDANCauchy++ algorithm.

This algorithm and some variants have been applied to the *"WCCI/GECCO 2020 Evolutionary Computation in Uncertain Environments: A Smart Grid Application"* which consists of a ERM problem considering uncertainty [30] and presented impressive results when compared to other metaheuristics.

2.1.5. HILL CLIMBING TO RING CELLULAR ENCODE-DECODE UMDA

Hill Climbing to Ring Cellular Encode-Decode UMDA (HC2RCEDUMDA) is a brand-new algorithm first introduced in the *"2021 Competition on Evolutionary Computation in the Energy Domain: Smart Grid Applications"* [31] that combines hill climbing and a ring cellular encode-decode UMDA (RCEDUMDA) [32]. This algorithm uses a cellular estimation of distribution algorithm similar to CUMDANCauchy. The search space is reduced by transforming continuous variables to categorical variables and then inverting the process, basically using an encoding-decoding method. This algorithm also estimates a univariate marginal distribution $p(x) = \prod_{i=1}^{l} p(x_i)$ from the neighborhoods' best individuals. A scaling method is used for the $p(x_i)$ to generate new individuals according to the probability of distribution used.

2.2. SMART GRID

Today's electric power system is already an old and aging system that has difficulty meeting energy needs and will most likely not be able to efficiently withstand the high penetration of renewable resources. Among the many shortcomings of the traditional electrical grid are the lack of automated analysis, mechanical switches that cause slow response times or poor visibility [33].

The existing power grid at times of higher demand tends to become overloaded and can lead to congestion problems in the lines. The periods where this type of situations occurs are usually known (commonly between 6pm and 9pm) and it is possible to determine the level of these loads through historical data. With the proliferation of electrical devices and with the high penetration of EVs that is occurring and that will tend to increase in the coming years the demand for electricity will also register this increase [34]. Since there are no energy storage systems to store energy on a large scale yet, producers will have to increase electricity generation to meet the high demand.

The continued integration of DER in the electricity grid, despite having certain advantages, such as the distributed generation (DG) that reduces losses in energy distribution, also brings serious problems for the traditional grid. One of the great disadvantages of this type of resource is the uncertainty associated with it, which can cause problems in voltage levels and frequency stability [35].

As such, the SG concept enters to make the electric grid more efficient and sustainable by promoting the integration of the previously mentioned resources. SG is an advanced digital power grid with a two-way power flow of electricity and information with adaptive, resilient, and sustainable capacities, capable of incorporating uncertainty associated with the DER [36].

Compared to the traditional network, the SG encourages the use of information and communication technologies (ICT) using devices such as smart meters, sensors, among others in order to increase network automation. This implementation makes the network more efficient in its operation due to the increase of information, which also makes the prices for the consumers of this network reduced due to the mechanisms, and models that surge to create greater stability in electricity production. Table 2 shows the comparison between a more traditional grid and the SG in terms of what each offers with its integration [37].

Table 2 Traditional electric grid versus the smart grid [37].

Traditional grid	**Smart grid**
Mechanization	Digitization
One-way communication	Two-way real-time communication
Centralized power generation	Distributed power generation
Radial network	Dispersed network
Less data involved	Large volumes of data involved
Small number of sensors	Many sensors and monitors
Less or no automatic monitoring	Great automatic monitors
Manual control and recovery	Automatic control and recovery
Less security and privacy concerns	Prone to security and privacy issues
Human attention to system disruptions	Adaptive protection
Simultaneous production and consumption of energy/electricity	Use of energy storage systems
Limited control	Extensive control system
Slow response to emergencies	Fast response to emergencies
Fewer user choices	Vast user choices

For the implementation of this type of grid, it is necessary to take into consideration certain concepts. Reference [38] gives some examples to take into account like: optimal sizing and placement of distribution system resources, optimal resource dispatching, integrated load and generation forecast, reconfiguration of the DN, and the integration of static and dynamic storage resources in the resource dispatch, just to name a few.

2.3. Electric vehicles

EVs are appearing in ever-increasing numbers due to existing agreements [39] and massive investments [40] in order to minimize pollution mainly in the transport sector, which is one of the main contributors for environmental issues with 16.2% of emissions [41]. Although this type of resource reduces environmental problems, its integration poses new challenges for the electric grid.

According to [42] at the end of 2020, the EV stock in the world passed the 10 million mark, an increase of around 3 million units from 2019 as Figure 6 shows, with more than 6.8 million battery EVs (BEVs), and 3.3 million plug-in hybrid EVs (PHEVs). One of the main contributors for the increase was Europe which had the highest increase out of all regions passing even China. Still, China remains the region with the highest stock of EVs in the world. Even in pandemic times the number of EVs increased significantly even compared to the increase from 2018 to 2019 which was only around 2.1 million.

Reference [42] proposes two scenarios forecasting the number of EVs on the roads by 2030. The first scenario is the Stated Policies Scenario, which integrates current government policies, that forecasts the EV stock to reach 145 million in 2030. The Sustainable Development Scenario is the second proposed scenario and incorporates what was established in the Paris Agreement. This scenario predicts that by 2030 there will be an EV stock of 230 million.

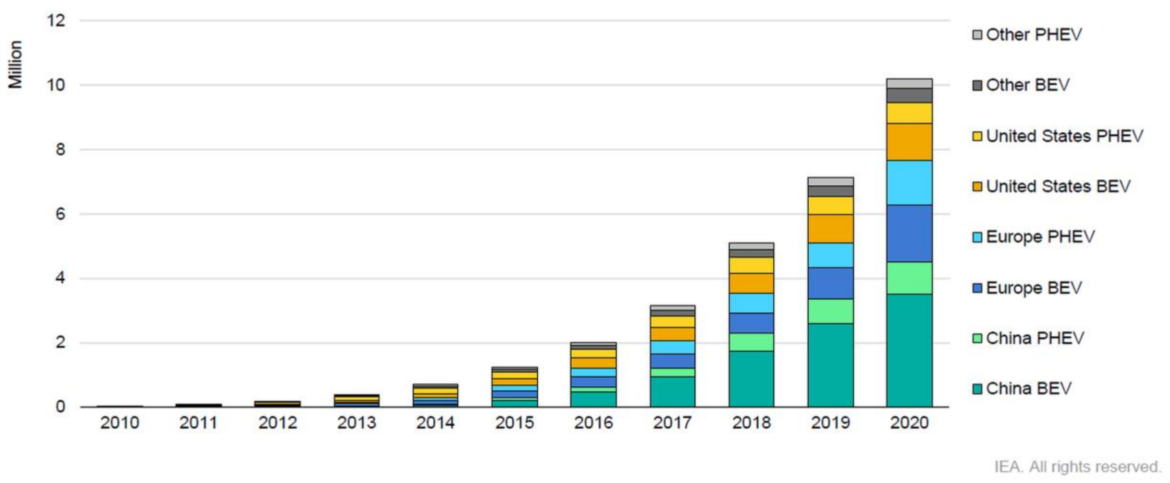


Figure 6 Number of electric cars in the major regions, 2010-20 [42].

With the statistics presented, the uncontrolled penetration of EVs could become a severe problem for the electric grid causing serious operational challenges, such as congestion and overloading for the grid. This situation is mainly caused by the uncertain pattern of these vehicles' users when charging (dumb charging). It is necessary to take advantage of the opportunities that this type of resources brings.

Figure 7 demonstrates the services provided by EVs at the transmission level, distribution level, and when it comes to renewables [43]. It is possible to observe that at distribution level DR programs (load shifting, peak shaving) can be implemented due to the high elasticity of EV load.

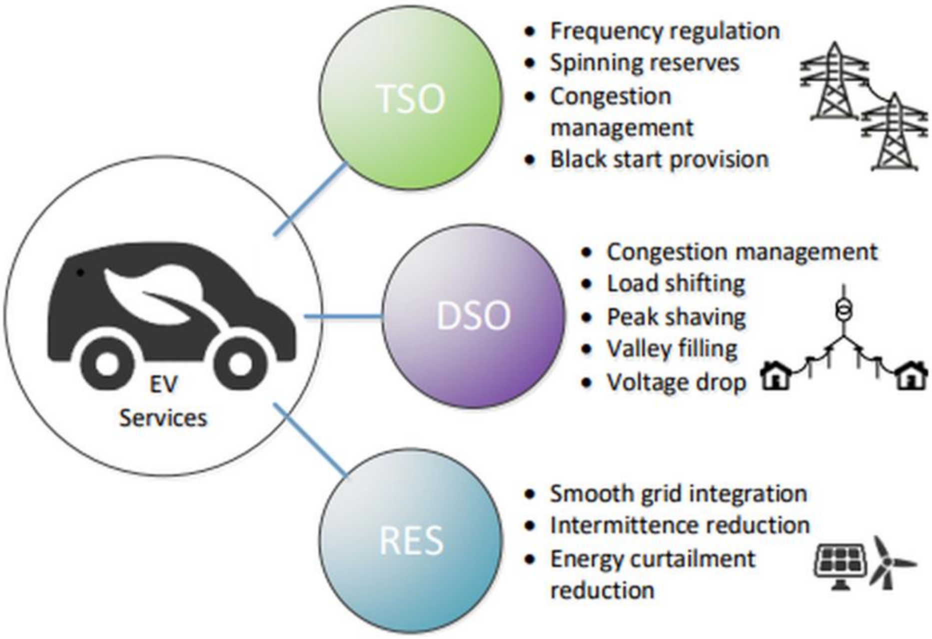


Figure 7 EV services provided for different parties in power systems [43].

2.4. ENERGY RESOURCE MANAGEMENT

Power grids evolve toward massively distributed electrical systems technologies with millions of nodes which are controllable. Transformative changes are taking place at the distribution stage, with the increasing integration of renewable technologies, energy storage systems (ESSs), and flexible loads such as EVs [44]. This demands that electric grids be modernized by operators and planners. The utility industry is investigating ways of exploiting DERs to boost network services, act as a catalyst for businesses at the delivery level and give clients innovative features. In this situation the energy resource management concept emerges to monitor and control these resources due to the uncertainty associated. Apart from the EVs another resource that will have a great increase is the PV production

[45]. Its high penetration in SGs also brings serious problems for the network's efficiency due to its volatility. Reference [46] presents a detailed analysis of both solar resource and PV power conceptual prediction techniques based on artificial intelligence (AI) with artificial neural networks (ANNs) being the main technique proposed. Also, implementations of these techniques in resource management in the SG concept are presented by the authors.

The work in [47] presents a network reconfiguration strategy and an optimal DER management to increase the robustness of the electrical network. Both methodologies have been applied to two IEEE DNs of 69 buses and 123 buses respectively with high penetration of DER. The resource management problem served to reduce the cumulative costs associated with the operation of DER and a decrease in load. In [48] it is proposed that an aggregator optimizes the programming of resources, however as it seeks to increase its profits, the demand can be reduced completely. The authors propose two techniques for the optimization of operational costs. The first is a DR function that serves as a restriction so that demand is always met, the second technique being the 0-1 knapsack problem that stores energy and turns off loads according to the DR function. Both techniques show similar results in terms of load reduction, but the proposed DR function presents better optimization time.

Reference [49] proposes an energy resource management system called Alternating Direction Method of the multiplier for the management of two controllers for a reduction of operational costs in a microgrid of 14 buses with high DG penetration. This scheduling was performed for a day-ahead time horizon and showed good results for islanded and grid-connected modes. The work in [50] proposes an optimal day-ahead scheduling under uncertainty considering six periods of four hours each. This scheduling aims to minimize the operating costs of a microgrid and minimize air pollution rates. The microgrid considered integrates several resources such as traditional energy sources, combined heat and power (CHP) generation, renewables, ESSs, and portable renewable energy. Stochastic programming is used for the uncertainty, and Augmented Epsilon-constraint method is used to solve the optimization problem which shows effective results. In [51] an energy management system is proposed for a network of microgrids, like Figure 8 shows. The energy resource management system considers a DR program for a better efficiency in the operation of the microgrids network, which is verified in a better stability and reduction in operational costs. Microgrids have a high DG penetration and flexible loads. To address the uncertainty of these resources, the authors have created multiple scenarios. Resources were scheduled for a 24-hour time horizon, i.e., a day-ahead scheduling.

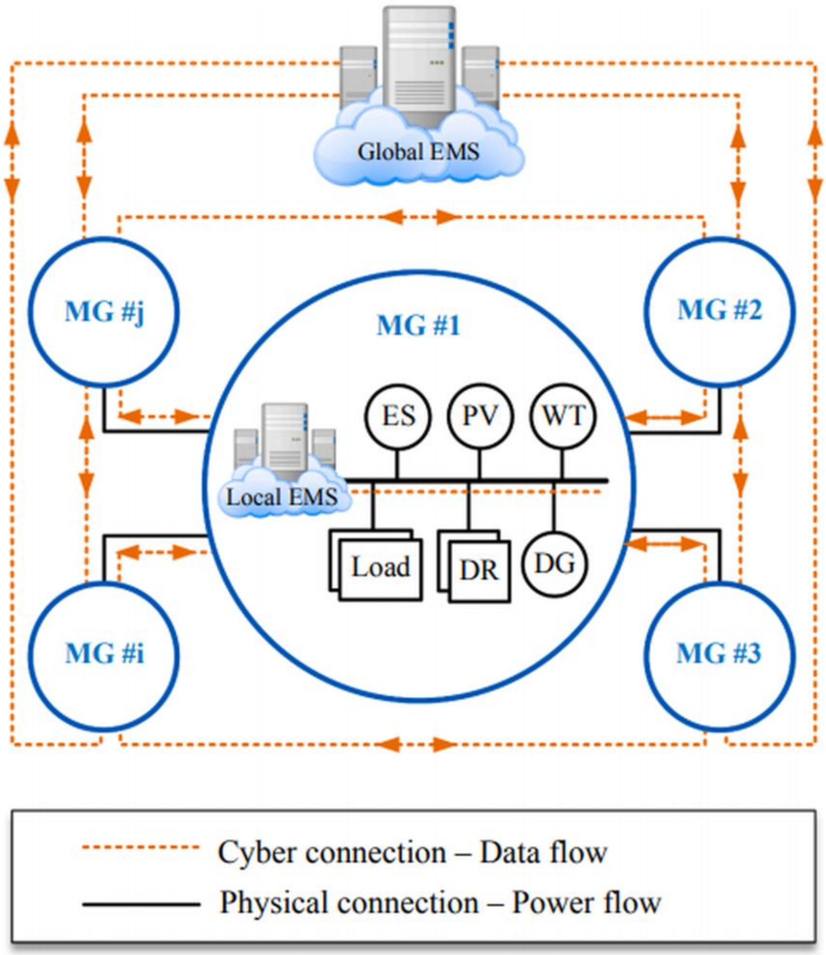


Figure 8 Structure of the proposed energy management for a network of microgrids [51].

As described previously, energy resource management is a concept that should be considered soon, given the high penetration of DER that will occur. This management allows a better efficiency in the operation of the electrical network which means a reduction in costs for the end-user. As these customers do not have the knowledge to make this management or because they are not interested there is an increase in tariffs that they receive. Here comes the concept of aggregator, which will seek to establish contracts with several customers and as such, it will make this resource management seeking to obtain profits. By carrying out this management of resources, a better quality of service to the end-user is provided since network efficiency improves; that is, it will pay more for this service. But by existing competition in this situation, retailers and other entities will be forced to give a better service to the end-user or reduce electricity costs.

2.5. DEMAND RESPONSE AND ELECTRIC VEHICLE FLEXIBILITY

DR programs can be considered with incentives for electricity users to reprogram their consumption patterns to improve grid efficiency [52].

Reference [53] separates DR programs in three different categories. The first category is the DR based on control mechanisms, centralized in which the users communicate, without interactions, directly with the power utility, and distributed mechanisms in which the users interact with each other. The second scheme is DR based on offered motivations. These schemes encompass price-based and incentive-based mechanisms. These two mechanisms are further explained in this section. Finally, the authors consider DR based on a decision variable scheme, which includes task scheduling-based DR and energy management-based DR. The first mechanism refers to controlling the activation time of the requested load, being able to decrease this time in peak consumption hours. The second mechanism is related to the reduction of specific load consumption.

Price-based DR is implemented through approved utility tariffs or contractual appointments in deregulated markets according to which the price of electricity varies over time so customers can adjust their load patterns. Incentive-based DR rewards customers for reducing their electric loads upon request or for giving the program administrator some level of control over the customer's electricity-using equipment. In this model, an encouragement exists by incentive payments to end-users due to their participation in the DR programs.

In this context EVs bring a high elasticity in their load, also known as EV flexibility. This flexibility allows the EV user to shift or reduce the vehicle's load consumption and even, in some cases, inject energy back to the grid. Several studies have emerged on this topic. The work in [54] proposes three business models for the flexibility of EVs. In the first business model, the service provider is the EV aggregator, and the customer is the DSO, the product being flexibility. The second business model makes the DSO the provider of this flexibility, the EV user, and the customer once again the DSO. The EV flexibility is traded in a marketplace. The final proposed model by this reference sees the EV aggregator requesting flexibility from the EV users, according to the amount sold by the aggregator to the DSO. In

[55] is considered a system with slow charging at home and fast-charging stations with and without batteries. The proposed mixed-integer linear programming unit commitment model finds an optimal time window to take advantage of EVs' high flexibility so that the problems caused by uncontrolled fast charging can be mitigated.

Considering this flexibility, the DR programs described above come in the EVs a huge applicability due to their elasticity. As such, several models of DR shaped for EVs appear. In this section two incentive-based programs specific for EVs are presented, smart charging (SC) and vehicle-to-grid (V2G).

2.5.1. SMART CHARGING

Uncontrolled charging of EVs (dumb charge) can cause problems for the proper operation of the network. This type of charging brings problems for the DSO, as the last will have to make significant investments to strengthen the network to satisfy the high energy demand that will arise. To mitigate these problems, the EV users need to adhere to a controlled charging, such as SC.

In this charging, the EV and the charging device must rely on minimum data exchanges. This data will then be shared to the charging station operator through the cloud as shown in Figure 9 [56]. Through SC, the charging stations can monitor, manage, and even restrict vehicles' charging to optimize energy consumption. EV users will participate in this type of charging, switching from dumb charging, due to economic incentives and convenience of charging.

Reference [57] presents an optimal day-ahead and real-time planning for smart charging. It combines both day-ahead planning with real-time coordination. By combining these two-time horizons, an improvement of grid stability and minimization of operational costs is achieved. The work in [58] proposes a utility model for joint EV user activity-travel scheduling and charging choices. This model considers the nuances of the EV user charging behavior. It concluded that service providers should consider incentive flexible charging behavior for their revenue management strategies.

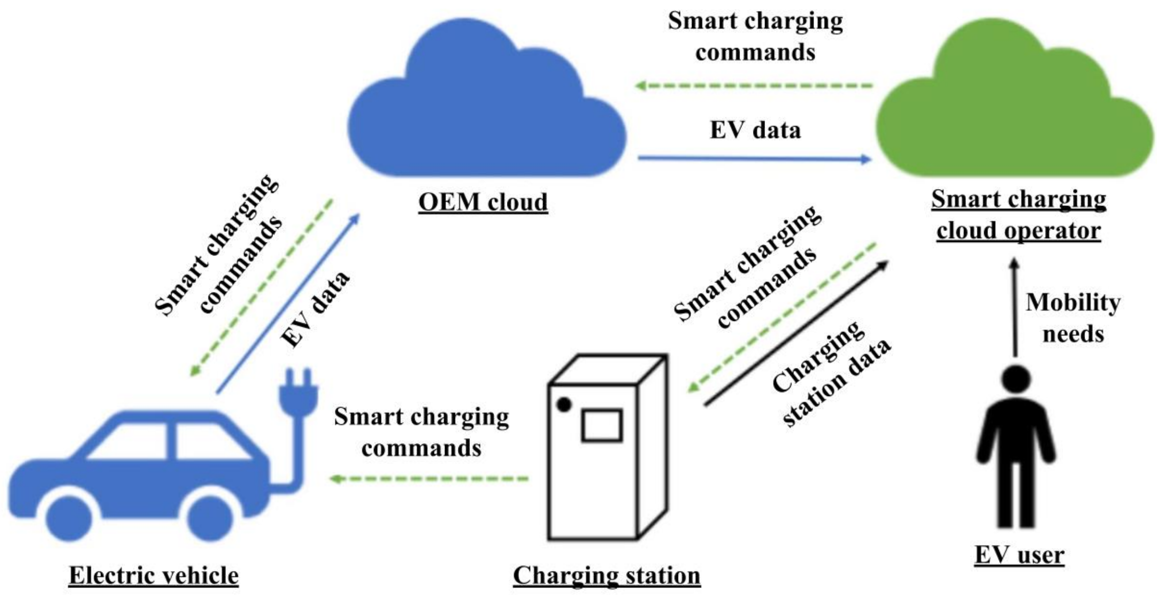


Figure 9 Typical data flow for a smart charging service [56].

2.5.2. VEHICLE-TO-GRID

The V2G strategy refers to when the EV becomes a load and a source of energy, i.e., it injects energy back into the grid when connected to it. It can help mitigate congestion problems because, with this technology, the vehicle can discharge the energy stored back to the grid during peak-hours and charge during off-peak hours [59]. Figure 10 shows a typical V2G architecture where the EV through an EV aggregator or an independent system operator (ISO) starts to work as an energy source, injecting power back to the grid with bidirectional power flow to supply service buildings or residential buildings when the demand is too high [60]. This mechanism is achieved with smart communication between all the involved players.

A significant drawback to implementing this type of model is that EV batteries will suffer a more significant degradation due to the constant switches between charging and discharging [61]. Due to this degradation, the incentive for EV owners must be higher than in other DR models. Because battery technology is not yet developed enough for this type of technology, this mode is seen in a low number of EVs. Even despite this technology being in such few EVs, several studies and surveys have been conducted to understand the benefits provided by V2G [62], [63].

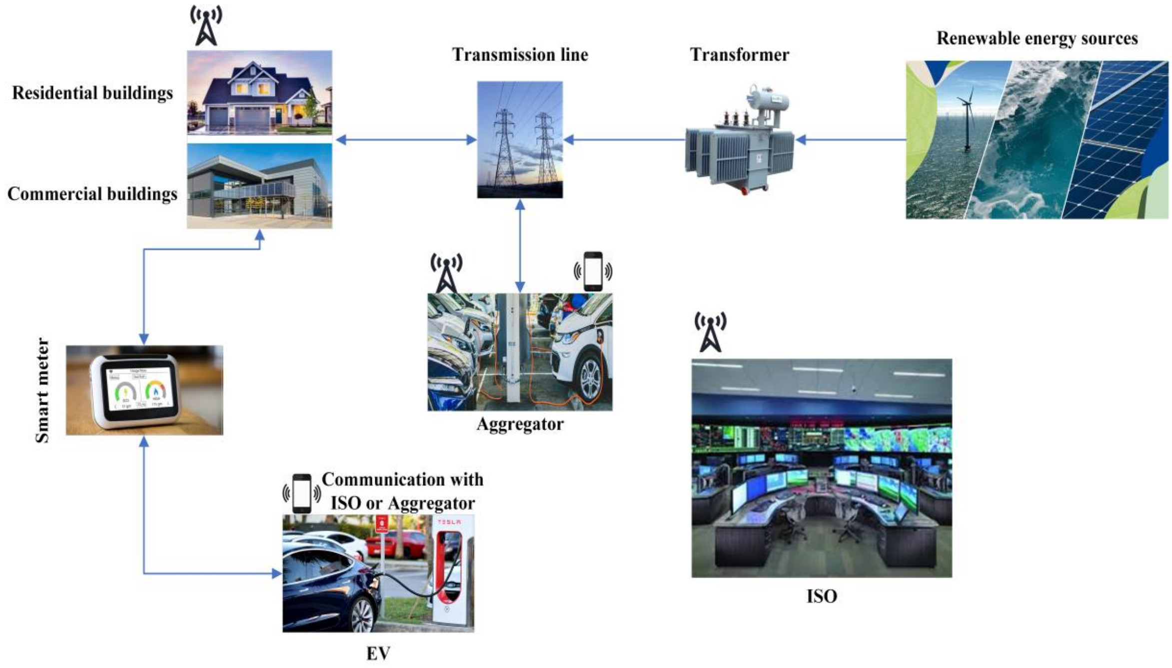


Figure 10 Example of a V2G system (adapted from [60]).

2.6. LOCAL ELECTRICITY MARKETS

Till recent times the electricity has been sold, bought, and traded in three different types of markets in a more liberalized way, as Figure 11 shows, wholesale (WS) market, balancing market, and retail market [64]. In the WS, energy is bought and sold to retailers or resellers, i.e., generation companies compete to sell electricity to buyers. In the retail market, there is the purchase and sale of energy to final consumers. The balancing market operated by the TSO that adjusts the supply/demand to balance the system to alleviate transmission issues. With the enormous penetration that is occurring and will continue to occur from DER. This type of penetration, the increase in demand for energy, a more customer-oriented market and the existence of prosumers (both consumers and producers) presents great challenges for existing markets [65]. This type of market is not fully designed for the integration of these resources, which leads to a decrease in the quality of electricity [66]. New market mechanisms emerge to deal with these challenges. The local electricity market (LEM) is a market that serves to exchange electricity that is produced and consumed in a neighborhood, that is, locally [67]. In this case, these exchanges make it possible to reduce existing losses during the transmission of energy on distribution lines, thus increasing the quality of energy. The LEMs, as they allow interaction between various players, give electricity producers an opportunity to increase their profits when selling electricity. This is not the case in the existing types of markets, as the excess electricity that is injected into the grid offers a low, sometimes zero remuneration for these individuals.

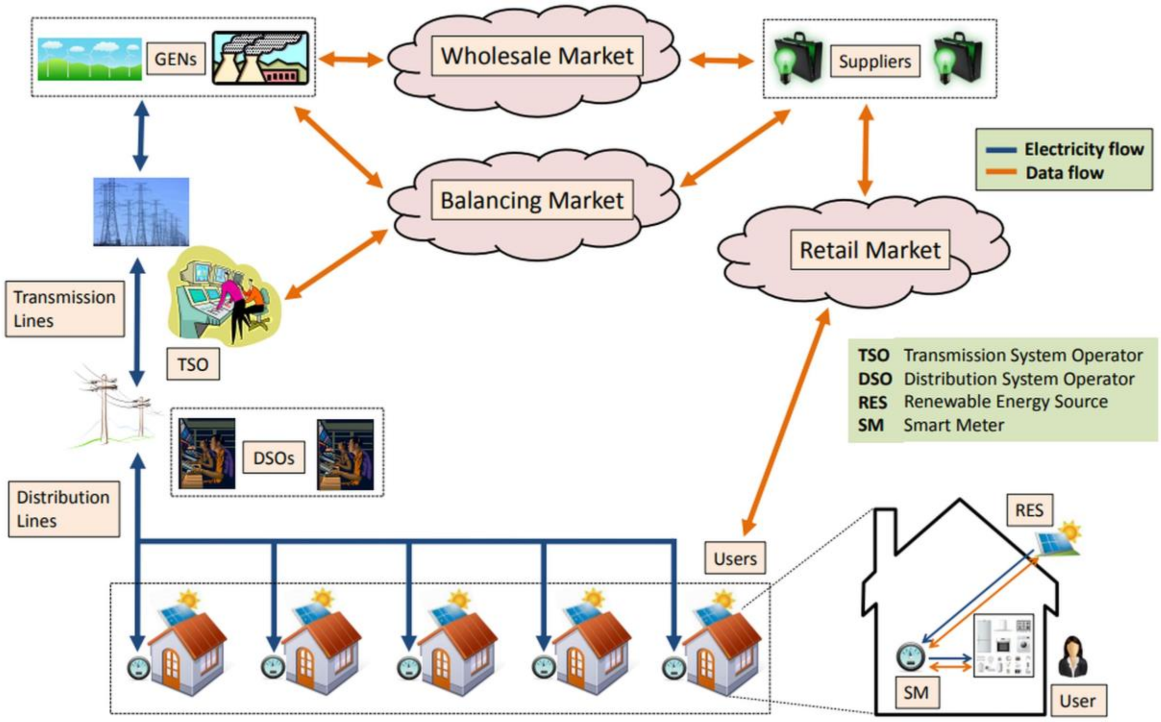


Figure 11 Electricity tradings in liberalised electricity markets [64].

Reference [68] proposes a communication system between the central electricity market (CEM), and renewable energy sources (RES) with the LEM as an intermediary between the two as Figure 12 shows. The authors in this paper also give three different coordination schemes between the LEM, and CEM. The first scheme is the DSO leader strategy, with a non-strategic DSO, and a strategic DSO. Non-strategic DSO is where the DSO has priority over the TSO, where he clears the LEM, allocates the flexible resources, and if demand is not fulfilled or the other way around (supply is not consumed) the DSO imports/exports that electricity. In strategic DSO, the DSO becomes the only aggregator in the DN which gives the DSO great market capacity which may cause competitive problems. The following scheme is the DSO follower, where the CEM has now the priority over the LEM fixing the prices or quantity of the power in the connection point between the transmission and distribution grids. The final coordination strategy is the TSO-DSO iteration where a coordination mechanism through iteratively communicating the generalized bid function for coordinating the economic dispatch of TSO and DSO.

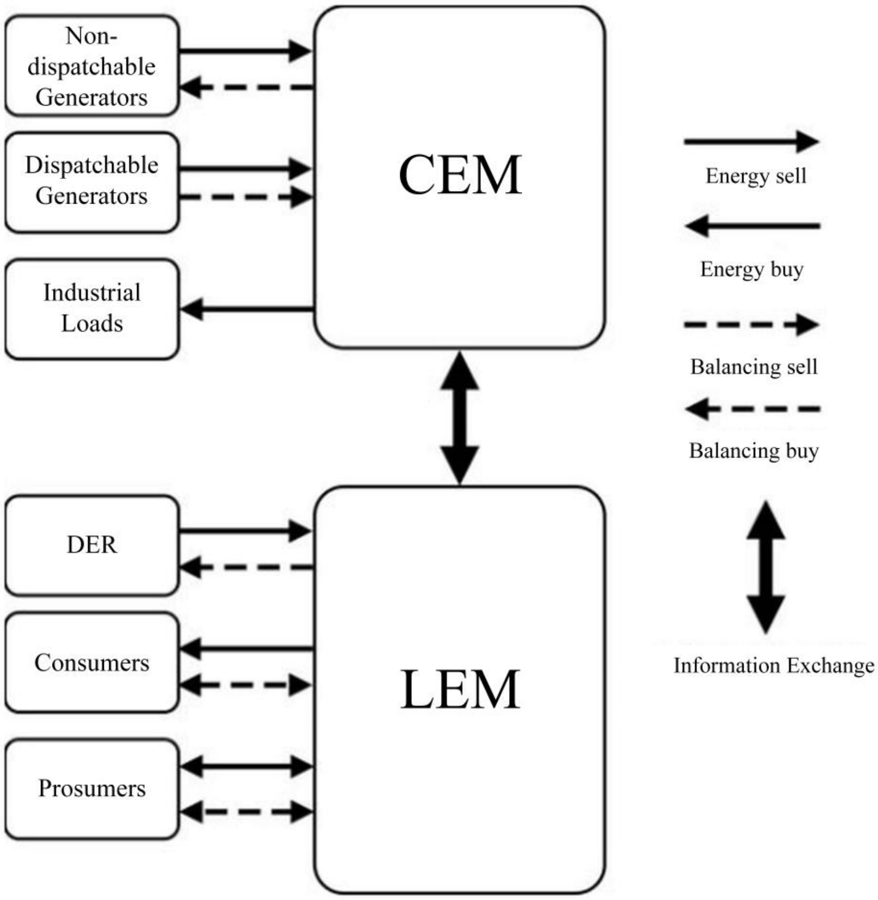


Figure 12 Market framework with local and central electricity and ancillary service market [68].

The paper in [3] presents a fully transactive energy system, integrating both WS market, and LEM. The authors start to solve the day-ahead energy resource management in the microgrid considering flexible loads (EVs, Energy Storage Systems (ESSs), DR) and market share. A WS market and a LEM are also shaped, as shown in Figure 13, considering uncertainty in the scenario generated, and bidding options in both domestic and WS markets. The management problem was solved using a two-stage stochastic model. In the first stage, the WS and LEM offers, as well as the dispatchable DG, are considered and in the second- stage, all the uncertainties are considered (EVs, ESSs, DR, etc.). Due to the uncertainty associated with some resources a Monte Carlo Simulation was applied to generate several scenarios using a probability distribution function (normal distribution). Then a scenario reduction technique was applied for each situation to aggregate those with similar characteristics, and to eliminate those with a low probability of occurrence. Finally, this paper analyzes the cost using three different scenarios: no market participation, only WS market participation and the combination of the WS and LEM, using flexibility in the load and no flexibility. As expected, the best results are obtained when the simulations consider the two markets, together with flexible loads. This paper includes EVs as flexible loads, which proves that their integration into LEMs is an added value for cost reduction.

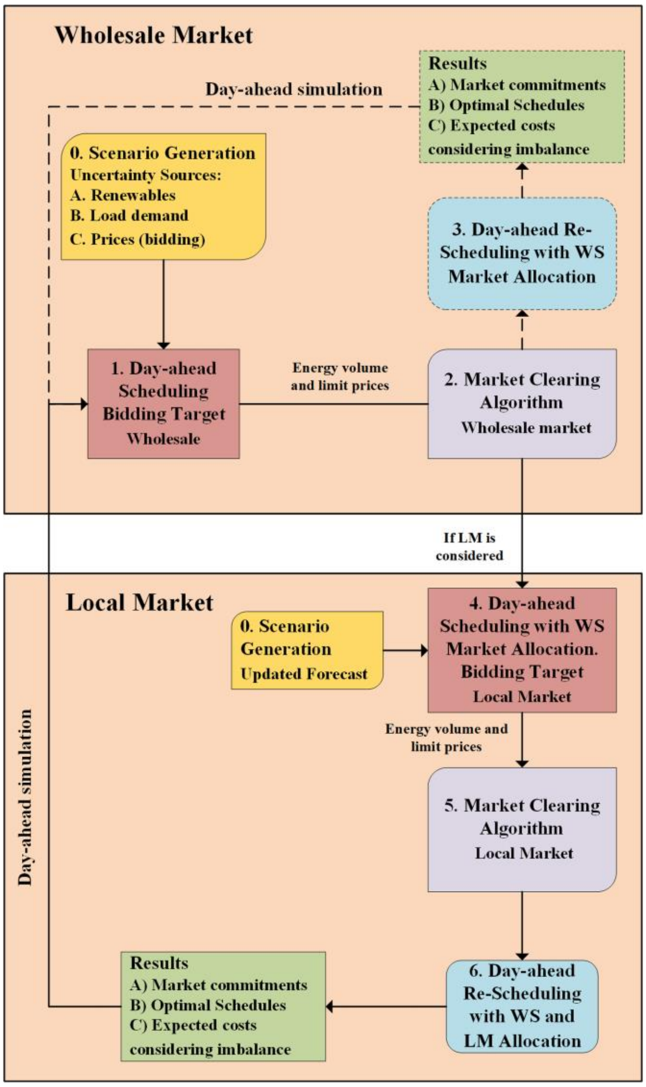


Figure 13 Wholesale and local market modulation (adapted from [3]).

The LEM then promotes the integration of the EVs. The product considered in local transactions is the flexibility of these vehicles. This flexibility can be transacted by an EV aggregator to the DSO for example, and the aggregator will request this flexibility from the EV user through monetary incentives. The interaction between these two entities is also provided by the LEMs.

The work in [69] shows new LM designs in a German case study. Due to the German regulations in this country the implementation of the current LMs designs brings unappealing financial profits to consumers and prosumers. The proposed model is formulated as a mixed complementary problem simulating a community of market players such as consumers, and prosumers. The authors propose a design that shows great potential to mitigate the effects of energy distribution, avoidance of system service charges, and end-user participation increase as the results show.

In [70] an optimal simulation of peer-to-peer business models for PV prosumers in a Swedish case study is presented. Simulations consider multiple ownership structures between players. This first structure is the local energy provider (LEP) where only one agent is the producer, and the others are simply consumers. The second proposed structure is the local energy community (LEC) where a communal plant is shared among all players or a selected group. The final is the LEM where multiple producers, consumers, and prosumers are considered increasing the structures complexity. The authors also proposed three business models incorporated in these ownership structures. The first one is called the LEC gratis where the electricity from the communal PV plant is given for free when available. LEC LCOE is where the electricity in the communal plant is set at production cost, and the obtained revenues are equally shared between shareholders. The final business model is the LEP n% and says that the single energy provider can set the prices within bounds. Results show that the PV prosumers achieve a great self-sufficiency in the considered models.

2.7. VALUE-AT-RISK

VaR is a concept widely used in economics to measure the risk of investment; that is, this parameter is a statistical mechanism that allows measuring the losses associated with a portfolio over a period of time for a given confidence level [71]. This parameter enables an excellent solution to be guaranteed in the occurrence of extreme scenarios, that is, scenarios with a high variation in characteristics and a low probability of occurrence [72].

Although VaR is a good tool for risk analysis, it has one major drawback in its implementation, which is the occurrence of these extreme scenarios beyond the confidence level. In this situation, the concept of CVaR which is an extension of VaR that allows evaluating the risk when the least likely scenarios occur beyond the confidence level [73].

This method presents greater security, which comes at a higher cost. The optimization implicit in this concept is a form of Pareto optimization with two objectives, the return, which in the case of this thesis is the aggregator costs, and the inherent risk.

Although this concept is widely associated with the economy and its aspects, it has begun to be implemented in the field of electric power systems. In [74], a smart energy hub model is proposed for a real case study incorporating different scenarios. This framework includes the uncertainty of natural-gas prices and electricity demand. A CVaR mechanism is applied to reduce the operational costs in the worst scenarios, that is, to control the operational risk of the system. Reference [75] presents a risk-averse strategy for microgrid planning. A two-stage stochastic approach is used for the planning of the different technologies incorporated in the microgrid with a mean-variance method to assess the risk. An optimal bidding framework for clusters of prosumers to maximize profits is proposed in [76]. A bi-level formulation is presented where the upper level is the maximization of profits when market trading in the day-ahead while the lower-lever intends to minimize energy costs of the prosumers. A CVaR mechanism is implemented to measure the risk associated with the energy sharing between prosumers and the day-ahead market prices.

2.8. CHAPTER CONCLUSIONS

In this chapter, several topics were presented that demonstrate relevance in consolidating the concept of energy resource management for DERs, especially EVs in an SG concept.First, contextualization of the various algorithms based on AI with a focus on EAs, especially HyDE-DF, which is adopted in this work. HyDE-DF was chosen due to its adaptive characteristics. The crossover and scaling parameters change according to the search performed by the algorithm. The desired algorithm also has good exploration and exploitation processes, as described, which is a plus for the intended purpose. Next, the SG concept was presented, and several statistics were presented that prove the increase and the challenges that the integration of EVs brings to the electrical grid. Energy resource management was another of the themes approached, presenting several works developed for the concept. The concepts of DR and EV flexibility were also discussed, as well as local transactions and their importance. It was then possible to conclude from the research carried out that the SG concept allows the electrical network to better manage DERs, such as renewables and EVs. This management is performed through optimization algorithms that obtain optimal scheduling of resources. This situation allows the minimization of electric network operational costs and reduction of congestion problems. This decrease is greater by implementing mechanisms of DR and local transactions. The concepts of VaR and CVaR were also studied. These concepts allow dealing with the inherent uncertainty in the problem and obtaining a solution that offers robustness and security in the results regarding the scenarios that represent the uncertainty of energy resource scheduling with the least possible risk when faced with the various scenarios considered. In the next chapter, the formulation for optimal resource management is proposed, considering the methodology adopted by multiple metaheuristics presented here. Concepts such as LEM transactions are also applied, and a formulation with risk assessment mechanisms is made to guarantee a more robust solution.

3. METHODOLOGY

This section presents the proposed methodology for the mathematical formulation, algorithm optimization, and uncertainty generation for the ERM problem in the day-ahead, intraday optimization, and a risk-based formulation for the day-ahead ERM.

3.1. ENERGY RESOURCE SCHEDULING FORMULATION

The proposed model for the optimization of the ERM problem on intraday starts by initially performing the day-ahead resource scheduling, as this solution is necessary for the hour-ahead model. As such, the day-ahead resource scheduling model is shown in Figure 14.

For the multiple aggregators to be able to perform day ahead ERM, it is necessary to acquire technical data for the various technologies associated with them. The technical data includes the distributed generation needed for the renewable generation aggregator load and DR contracts for the load aggregators, EV data for the EV aggregator, and other shared resources that all aggregators have access to. The forecasted data of uncertain resources is necessary for the model, as Figure 14 presents, generated through a set of scenarios. The dedicated energy resources are then managed for the next 24 hours by these aggregators.

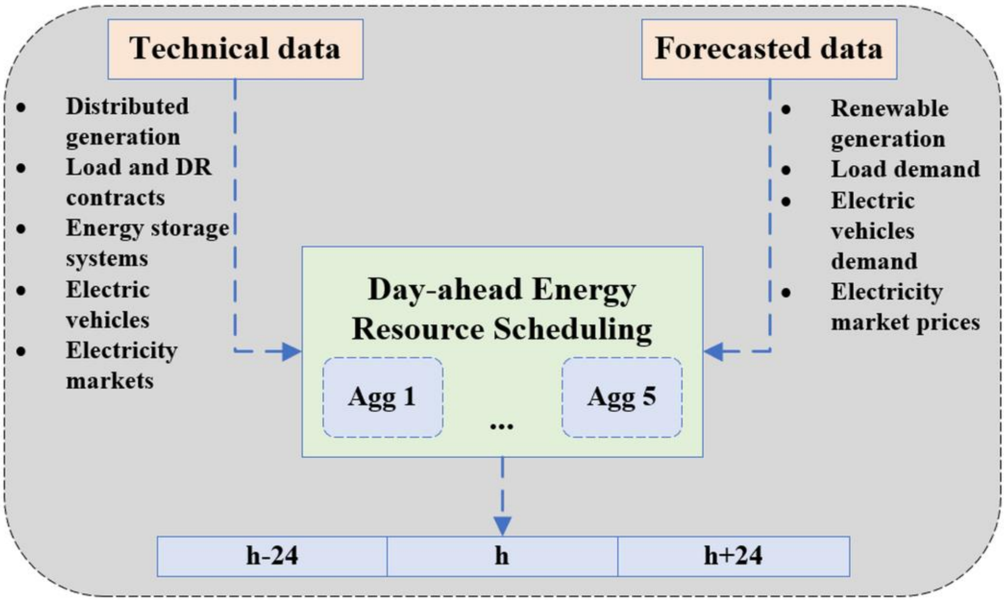


Figure 14 Day-ahead ERM model.

Regarding to the mathematical formulation of the day-ahead ERM for the multiple aggregators considering what is proposed in (3) and (4), the terms of the total costs in each scenario s can be given by:

$$Z_{OC}^{s} = \sum_{t=1}^{T}\left[\sum_{i\in\Omega_{DG}^{d}} P_{DG(i,t)} \cdot C_{DG(i,t)} + \sum_{k=1}^{N_k} P_{ext(k,t)} \cdot C_{ext(k,t)}\right] \cdot \Delta t \qquad (3)$$

$$+ \sum_{t=1}^{T}\left[\begin{array}{c} \sum_{i\in\Omega_{DG}^{nd}} P_{DG(i,t,s)} \cdot C_{DG(i,t)} + \sum_{e=1}^{N_e} P_{Disch(e,t,s)} \cdot C_{Disch(e,t)} + \\ \sum_{v=1}^{N_v} EV_{Disch(v,t,s)} \cdot EVC_{Disch(v,t)} + \sum_{l=1}^{N_l} P_{curt(l,t,s)} \cdot C_{curt(l,t)} + \\ \sum_{r=1}^{N_r} P_{ENS(r,t,s)} \cdot C_{ENS(r,t)} + \sum_{i=1}^{N_i} P_{GCP(i,t,s)} \cdot C_{GCP(i,t)} \end{array}\right] \cdot \Delta t \quad \forall s.$$

$$Z_{In}^{s} = \sum_{t=1}^{T}\left[\sum_{m=1}^{N_m}\left(P_{Buy(m,t)} - P_{Sell(m,t)}\right) \cdot MP_{(m,t,s)}\right] \cdot \Delta t \quad \forall s. \qquad (4)$$

In (3) and (4), the total number of periods is represented by the symbol T, the set of dispatchable generation is referred to as Ω_{DG}^{d}. The number of external suppliers is given as N_k and the total number of scenarios is N_s. N_e represents the number of ESSs. The number of EVs is called N_v, and the number of loads is N_l. N_r represents the number of resources where energy is not supplied (ENS), and N_i is the number of distributed generators. The symbol N_m denotes the number of WS markets. The active power generation is given by P_{DG} (MW), P_{ext} is the external power supplied (MW). P_{Disch} represents the ESS power discharge (MW), EV_{Disch} is the EV discharge power (MW). The power reduction of load l is given by P_{curt} (MW), P_{ENS} represents the non-supplied demand, in periods t of resource r (MW), and the excess of DG units' i generation is P_{GCP} (MW). P_{Buy} represents power purchased from the market (MW), P_{Sell} represents power sold to the market (MW). C_{DG} represents the cost of distributed generation (m.u./MWh), C_{ext} represents the cost of an external supplier (m.u./MWh), and C_{Disch} represents the cost of ESS discharging (m.u./MWh). The cost of EV discharge is EVC_{Disch} (m.u./MWh), and the load curtailment cost is C_{curt} (m.u./MWh). The cost of energy not supplied (ENS) is represented by C_{ENS} (m.u./MWh), whereas the penalty for excess energy is represented by C_{GCP} (m.u./MWh). The WS electricity market price is MP (m.u./MWh). Δt is the time step which in this case corresponds to 1 hour.

The optimization algorithms try to find a global minimum of the expected cost as it is described in (38). It's worth noting that each aggregator is in charge of a specific service in the DN; as a result, certain parameters of (3) become zero and disappear depending on the aggregator's energy resources. For the proposed load aggregators, the EV term and renewable energy term disappear. For the renewable generation aggregator, the EV term and load curtailment cost term disappear, and for the EV aggregator the terms involving non-dispatchable generation, and load reduction become zero.

The objective function (OF) of the scheduling problem (equations (3)-(4)) is subject to certain restrictions. The constraints are as follows:

Active power balance constraint: In each period t the generation must be equal to the consumption for each scenario s:

$$\left[\begin{array}{c} \sum_{i\in\Omega_{DG}^{d}} P_{DG(i,t)} + \sum_{k=1}^{N_k} P_{ext(k,t)} + \sum_{i\in\Omega_{DG}^{nd}} (P_{DG(i,t,s)} - P_{GCP(i,t,s)}) + \\ \sum_{r=1}^{N_r} P_{ENS(r,t,s)} + \sum_{l=1}^{N_l} (P_{curt(l,t,s)} - P_{load(l,t,s)}) + \sum_{e=1}^{N_e} (P_{Disch(e,t,s)} - P_{Char(e,t,s)}) + \\ \sum_{v=1}^{N_v} (EV_{Disch(v,t,s)} - EV_{Char(v,t,s)}) - \sum_{m=1}^{N_m} (P_{Buy(m,t)} - P_{Sell(m,t)}) \end{array}\right] = 0 \quad \forall t, \forall s. \tag{5}$$

Where P_{load} is the forecasted active power of the loads (MW), P_{Char} represents the ESS charging power (MW), and EV_{Char} is the EV charging power (MW). Since P_{ENS} and P_{GCP} represent the penalties if (5) is not met. In this situation a special weight is given to these parameters otherwise a penalty of 100 m.u. per period is added to (3) in the terms associated with the imbalances. Depending on the aggregator, some of these terms are zero like in (3).

Power generation constraints: Maximum and minimum limits for active power generation in each period t is as follows:

$$P_{DGmin(i,t)} \cdot x_{DG(i,t)} \leq P_{DG(i,t)} \quad \forall i \in \Omega_{DG}^{d}, \forall t. \tag{6}$$

$$P_{DG(i,t)} \leq P_{DGmax(i,t)} \cdot x_{DG(i,t)} \quad \forall i \in \Omega_{DG}^{d}, \forall t. \tag{7}$$

The external supplier maximum and minimum limits in each period t can be modeled as:

$$P_{extmin(k,t)} \cdot x_{ext(k,t)} \leq P_{ext(k,t)} \quad \forall k, \forall t. \tag{8}$$

$$P_{ext(k,t)} \leq P_{extmax(k,t)} \cdot x_{ext(k,t)} \quad \forall k, \forall t. \tag{9}$$

The non-dispatchable generation formulated according to each scenario s:

$$P_{DG(i,t,s)} = P_{DG_{nd}(i,t,s)} \cdot x_{DG(i,t)} \quad \forall i \in \Omega_{DG}^{nd}, \forall t, \forall s. \tag{10}$$

Where P_{DGmin} is the minimum active power of dispatchable generation unit i in period t (MW), P_{DGmax} is the maximum active power of dispatchable generation unit i in period t (MW). The minimum and maximum active power generation of external supplier unit k in period t are represented by P_{extmin}(MW), and P_{extmax} (MW) respectively. $P_{DG_{nd}}$ is the forecasted renewable generation power of non-dispatchable generation unit i in period t (MW). The binary variables representing the state of DG, and external supplier units is given by x_{DG}, and x_{ext} respectively. The renewable generation aggregator is the only aggregator subject to constraint (10).

Energy storage system constraints: The battery balance constraint for each ESS unit is defined as follows:

$$E_{stored(e,t,s)} = E_{stored(e,t-1,s)} + \eta_{c(e)} \cdot P_{Char(e,t,s)} \cdot \Delta t - \frac{1}{\eta_{d(e)}} \cdot P_{Disch(e,t,s)} \cdot \Delta t \quad \forall e, \forall t, \forall s. \tag{11}$$

The maximum discharge and charge limits for each ESS unit can be formulated as:

$$P_{Disch(e,t,s)} \leq P_{Dischmax(e,t)} \quad \forall e, \forall t, \forall s. \tag{12}$$

$$P_{Char(e,t,s)} \leq P_{Charmax(e,t)} \quad \forall e, \forall t, \forall s. \tag{13}$$

The maximum battery capacity limit for each ESS unit can be written as:

$$E_{stored(e,t,s)} \leq E_{BatCap(e)} \quad \forall e, \forall t, \forall s. \tag{14}$$

The minimum energy stored required to be guaranteed at the end of period t can be modeled as:

$$E_{stored(e,t,s)} \geq E_{MinCharge(e,t)} \quad \forall e, \forall t, \forall s. \tag{15}$$

Where E_{stored} is the energy stored in each ESS unit e in period t for scenario s (MWh). The charging efficiency and discharging efficiency of ESS unit e is given by $\eta_{c(e)}$, and $\eta_{d(e)}$ (%). $P_{Dischmax}$ is the maximum active discharge rate of ESS e in period t (MWh), $P_{Charmax}$ is the maximum active charge rate of ESS e in period t (MWh). E_{BatCap} is the maximum energy capacity allowed by ESS e (MWh), and $E_{MinCharge}$ minimum energy stored required in ESS unit e in period t (MWh).

Electric vehicle constraints: The constraints for the EVs are similar to the ESSs because EVs are considered as virtual batteries. The battery balance constraint of each individual EV is formulated as follows:

$$E_{stored(v,t,s)} = E_{stored(v,t-1,s)} + \eta_{c(v)} \cdot EV_{Char(v,t,s)} \cdot \Delta t - \frac{1}{\eta_{d(v)}} \cdot EV_{Disch(v,t,s)} \cdot \Delta t \quad \forall v, \forall t, \forall s. \tag{16}$$

The discharging and charging limits for each EV are represented by the following:

$$EV_{Disch(v,t,s)} \leq EV_{Dischmax(v,t)} \quad \forall v, \forall t, \forall s. \tag{17}$$

$$EV_{Char(v,t,s)} \leq EV_{Charmax(v,t)} \quad \forall v, \forall t, \forall s. \tag{18}$$

The maximum battery capacity limit for each EV unit is given by:

$$E_{stored(v,t,s)} \leq E_{BatCap(v)} \quad \forall v, \forall t, \forall s. \tag{19}$$

The minimum energy stored required to be guaranteed at the end of period t for each EV can be defined as:

$$E_{stored(v,t,s)} \geq E_{MinCharge(v,t)} \quad \forall v, \forall t, \forall s. \tag{20}$$

Where E_{stored} is the energy stored in each EV unit e in period t for scenario s (MWh). The charging efficiency and discharging efficiency of EV unit v is given by $\eta_{c(v)}$, and $\eta_{d(v)}$ (%). $EV_{Dischmax}$ is the maximum active discharge rate of EV v in period t (MWh), $EV_{Charmax}$ is the maximum active charge rate of ESS v in period t (MWh). E_{BatCap} is the maximum energy capacity allowed by ESS v (MWh), and $E_{MinCharge}$ minimum energy stored required in ESS unit v in period t (MWh). The constraints (16)-(20) only apply to the EV aggregator, for the remaining all values are set to zero.

Demand response constraints: The demand response model, namely direct load control where consumption is reduced by the end-user in exchange for an incentive. The maximum amount of load that can be reduced can be formulated as:

$$P_{curt(l,t,s)} \leq P_{DRmax(l,t)} \quad \forall l, \forall t, \forall s. \tag{21}$$

Where P_{DRmax} is the maximum limit of active power reduction in load l for period t. The three proposed aggregators are the ones affected by (21).

Electricity market constraints: The WS electricity market is the only assumed existing market in the day-ahead problem. The maximum and minimum amounts of energy that can be bought and sold in the electricity market are given by:

$$P_{Sell(m,t)} \geq P_{Sellmin(m,t)} \cdot x_{Sell(m,t)} \quad \forall m, \forall t. \tag{22}$$

$$P_{Sell(m,t)} \leq P_{Sellmax(m,t)} \cdot x_{Sell(m,t)} \quad \forall m, \forall t. \tag{23}$$

$$P_{Buy(m,t)} \geq P_{Buymin(m,t)} \cdot x_{Buy(m,t)} \quad \forall m, \forall t. \tag{24}$$

$$P_{Buy(m,t)} \leq P_{Buymax(m,t)} \cdot x_{Buy(m,t)} \quad \forall m, \forall t. \tag{25}$$

Where $P_{Sellmin}$ and $P_{Sellmax}$ are the minimum and maximum limits of energy offers in market m for period t. P_{Buymin} and P_{Buymax} are the minimum and maximum limits of energy bids in m for period t. The state of market sell/buy is given by the two binary variables x_{Sell}, and x_{Buy} respectively. The action of selling and buying energy in the market cannot be made simultaneously, so an additional constraint is proposed where:

$$x_{Sell(m,t)} + x_{Buy(m,t)} \leq 1 \quad \forall m, \forall t. \tag{26}$$

When it comes to the intraday methodology Figure 15 depicts a resource schedule planning diagram in the hour-ahead sense. The technical data acquired for each aggregator is similar to the day-ahead model but in this case with a 1-hour resolution with periods of 15 minutes. The hour-ahead ERM model requires data and contracts closed in the day-ahead time horizon, which is injected into the intraday model. In this case the energy contracted to the external supplier, and the WS market energy bought/sold in the day-ahead. The level of charge (SoC) of the EV and energy storage systems (ESSs) of the hour h-1, in the last period of 15 minutes is supplied as the initial SoC of the hour h (first 15-minute period) for the following four-time slots (h+1), with a 15-minute time slot resolution.

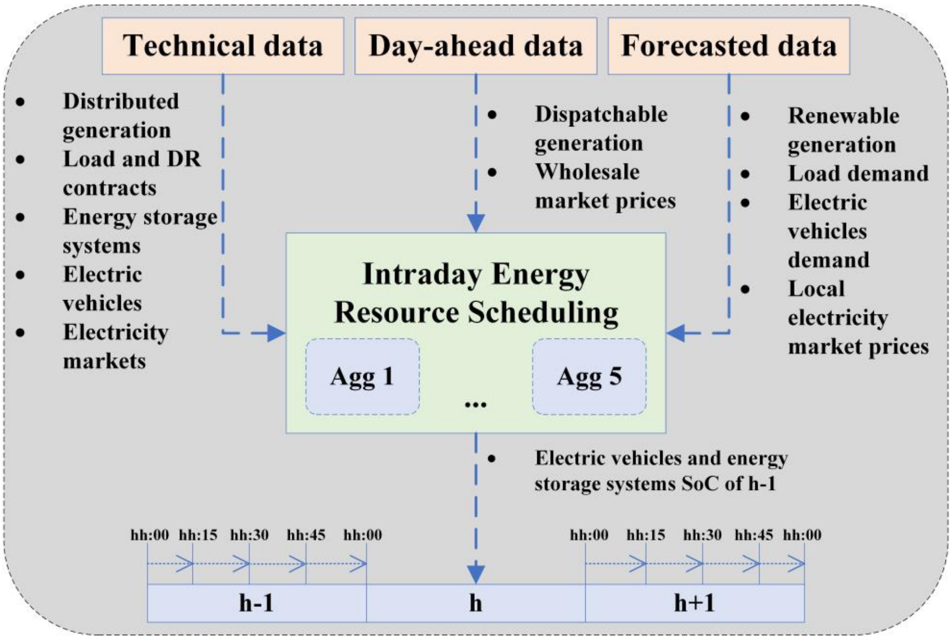


Figure 15 Hour-ahead ERM model.

The mathematical formulation for the intraday ERM problem is somewhat similar to the day-ahead formulation, but here the time step (Δt) is equal to 15 minutes which corresponds to $\frac{1}{4}$ of an hour. The LEM is also introduced in this model for energy transactions to meet the active power balance constraint. In this case, (4) is reformulated as:

$$Z_{In}^{s} = \sum_{t=1}^{T} \left[\begin{array}{l} \sum_{m=1}^{N_m} \left(P_{Buy(m,t)} - P_{Sell(m,t)}\right) \cdot MP_{(m,t,s)} + \\ \sum_{lm=1}^{N_{lm}} \left(M_{Buy(lm,t)} - M_{Sell(lm,t)}\right) \cdot LEM_{(lm,t,s)} \end{array} \right] \cdot \Delta t \quad \forall s \in N_s. \tag{27}$$

Where N_{lm} is the number of LEMs, M_{Buy}, and M_{Sell} are the amount of power bought and sold in the LEM in each period t. The LEM parameter is the LEM prices for period t which depends on scenario s.

New constraints are introduced to control de offers and bids made in the LEM.

$$M_{Sell(m,t)} \geq M_{Sellmin(m,t)} \cdot x_{LMSell(m,t)} \quad \forall lm, \forall t. \tag{28}$$

$$M_{Sell(m,t)} \leq M_{Sellmax(m,t)} \cdot x_{LMSell(m,t)} \quad \forall lm, \forall t. \tag{29}$$

$$M_{Buy(m,t)} \geq M_{Buymin(m,t)} \cdot x_{LMBuy(m,t)} \quad \forall lm, \forall t. \tag{30}$$

$$M_{Buy(m,t)} \leq M_{Buymax(m,t)} \cdot x_{LMBuy(m,t)} \quad \forall lm, \forall t. \tag{31}$$

$$x_{LMSell(m,t)} + x_{LMBuy(m,t)} \leq 1 \quad \forall m, \forall t. \tag{32}$$

Where $M_{Sellmin}$, and $M_{Sellmax}$ are the minimum and maximum limits for selling imposed to the LEM m in period t, and M_{Buymin}, M_{Buymax} are the minimum and maximum bidding capacity for the LEM m in period t. In (32) the binary variables x_{LMSell}, and x_{LMBuy} represent the state of the LEM because bidding and offering cannot occur at the same time.

As shown in Figure 16 the external supplier and dispatchable generation values are closed through contracts made in the day-ahead optimization. In this situation the external supplier and dispatchable generation power in the intraday is formulated as follows:

$$P_{DG(i,t)} = P_{DG(i,t)}^{DA} \cdot x_{DG(i,t)}^{DA} \quad \forall i \in \Omega_{DG}^{d}, \forall t. \tag{33}$$

$$P_{ext(k,t)} = P_{ext(k,t)}^{DA} \cdot x_{ext}^{DA} \quad \forall k, \forall t. \tag{34}$$

Where P_{DG}^{DA} is the amount of active power obtained in the day-ahead optimization for each dispatchable generation unit i for each period t. P_{ext}^{DA} is the amount of active power obtained in the day-ahead optimization for each external supplier unit k for each period t. The binary variables x_{DG}^{DA}, and x_{ext}^{DA} are also set to the obtained day-ahead values for the state of the generators.

The WS market offers, and bids are according to values negotiated in the day-ahead. The hour-ahead offers and bids for the WS market can be written as:

$$P_{Sell(m,t)} = P_{Sell(m,t)}^{DA} \cdot x_{Sell(m,t)}^{DA} \quad \forall m, \forall t. \tag{35}$$

$$P_{Buy(m,t)} = P_{Buy(m,t)}^{DA} \cdot x_{Buy(m,t)}^{DA} \quad \forall m, \forall t. \tag{36}$$

Where P_{Sell}^{DA} is the amount of sold power negotiated in the day-ahead in market m for period t, and P_{Buy}^{DA} is the amount of bought power negotiated in the day-ahead in market m for period t. The state of the market in the day-ahead is given by x_{Sell}^{DA}, and x_{Buy}^{DA} which are also fixed for the intraday optimization (previously subject to (26)). The values in (33)-(36) are decided in the day-ahead for each hour, so for each 15 minutes time slot of an hour, it is assumed the same value negotiated in the day-ahead.

3.2. RISK-BASED ERM

A risk-based methodology is applied to the proposed ERM model when it comes to the day-ahead. This section shows the formulation of a risk-neutral strategy and a risk-averse strategy for an aggregator. The risk-neutral method does not incorporate the parameters that measure risk. On the other hand, the risk-averse uses these parameters to guarantee a better solution in the occurrence of extreme events.

3.2.1. RISK-NEUTRAL FORMULATION

A risk-neutral strategy considered for the day-ahead ERM considers the uncertain behavior of an aggregator's technologies such as renewable generation, load consumption, market prices, EV consumption behavior. In this case, the stochastic behavior of these parameters is considered in the approach used through various scenarios with an associated probability of occurrence, as will be described in subchapter 3.4.

When the risk is not considered, the formulation of the scheduling of this aggregator is done based on the expected scenario. The cost and the value of the OF when a risk aversion strategy is not considered is given by the expected cost and its formulation is given by:

$$Z_{tot}^{s} = Z_{OC}^{s} - Z_{In}^{s} + P^{s}. \tag{37}$$

$$Z_{Ex} = \sum_{s=1}^{N_s} (\rho_s \times Z_{tot}^{s}) . \tag{38}$$

Where Z_{tot}^{s} is the total OF value of each scenario s given by the difference between operational costs in each scenario (Z_{OC}^{s}), the income in each scenario (Z_{In}^{s}), and the penalties for bounds violations (P^{s}). The expected OF cost is represented by Z_{Ex}, and ρ_s is the probability of the respective scenario.

3.2.2. RISK-AVERSE FORMULATION

A risk-aversion strategy considers the risk associated with the uncertainty of the previously mentioned technologies. In this situation, the aggregator takes into account the worst-case scenario when day-ahead scheduling is performed. This situation is due to extreme scenarios, scenarios with a low probability of occurrence, but that significantly affect the scheduling because they present significant variations compared to the other scenarios, that is, scenarios with high consequences. These scenarios can represent a high peak in market prices, load demand, a reduction, or even the absence of renewable production.

In this work the CVaR is implemented, which is a risk measurement mechanism that will take into account these extreme events in order to minimize their impact. CVaR adds to the concept of VaR because VaR can only measure risk when the expected cost Z_{Ex} does not exceed the confidence level (α) for all simulated scenarios. CVaR$_\alpha$ allows to measure risk past the confidence level, that it, this parameter is added to the expected cost Z_{Ex} when the value of the OF of the scenarios is higher than $Z_{Ex} + VaR_\alpha$ which gives them the notation of conditional expected cost. For the simulations involving risk-aversion α was considered to be 95% which is a typical value for this parameter [77].

The VaR$_\alpha$, CVaR$_\alpha$, and z_{eX} concepts are represented in Figure 16 through the normal and cumulative probability distribution functions.

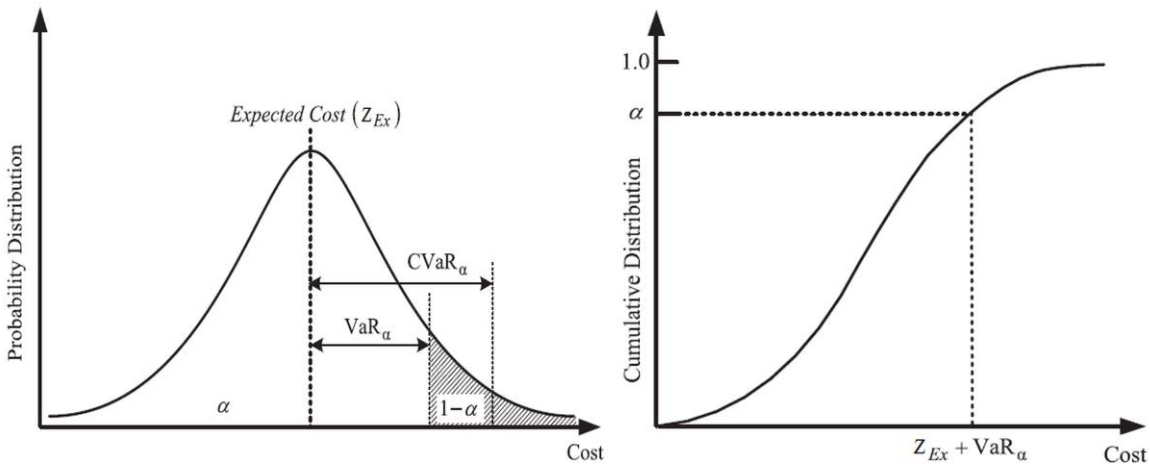


Figure 16 Graphical representation of VaR, CVaR and Z_{Ex} through normal and cumulative distribution functions [78].

Considering the cost of each scenario and for the α value already known, the VaR_α was calculated using the cumulative probability distribution function as shown in Figure 16 after knowing the value of the expected cost as calculated in (38).

As previously mentioned $CVaR_\alpha$ is an additional cost that is added to Z_{Ex} in (1-α)% of the scenarios with the highest costs. After calculating the value of VaR_α the $CVaR_\alpha$ is calculated using the following formulation [78]:

$$CVaR_\alpha(Z_{tot}^s) = VaR_\alpha(Z_{tot}^s) + \frac{1}{1-\alpha}\sum_{s=1}^{N_s} \rho_s \times \varphi. \tag{39}$$

Where φ is given by:

$$\varphi = \begin{cases} Z_{tot}^s - Z_{Ex} - VaR_\alpha(Z_{tot}^s), & if\ Z_{tot}^s \geq Z_{Ex} + VaR_\alpha(Z_{tot}^s)\ \forall s \in N_s \\ 0, & otherwise \end{cases}. \tag{40}$$

This parameter is associated with the cost in the worst scenarios, that is, when the cost of each scenario s exceeds the expected cost with the addition of the VaR_α value. If the opposite occurs φ is given the value of zero.

Taking this parameter into account, the OF of the scheduling problem varies according to the level of risk aversion considered. The model of the OF in this situation is then given by:

$$OF = Z_{Ex} + \beta \cdot CVaR_\alpha(Z_{tot}^s). \tag{41}$$

In this situation the β parameter represents the percentage of aversion to the risk. This parameter can vary between 0 and 1. When it is 0 the OF value is only equal to the expected cost which means that it is a risk-neutral strategy. β being 1 means that the strategy has 100% aversion to risk presenting the safest solution when it comes to the worst scenarios.

3.3. OPTIMIZATION TECHNIQUE

The metaheuristic optimization of the ERM problem follows the same framework despite the multiple used algorithms. Here the main function used for the hour-ahead energy scheduling, the encoding of the individuals, and the fitness function description are shown.

3.3.1. PROGRAM STRUCTURE

The flowchart of the primary function for the hour-ahead ERM is shown in Figure 17. The function starts by selecting the aggregator for which you want to optimize the energy resources, where it loads the day-ahead results obtained for the aggregator in question.

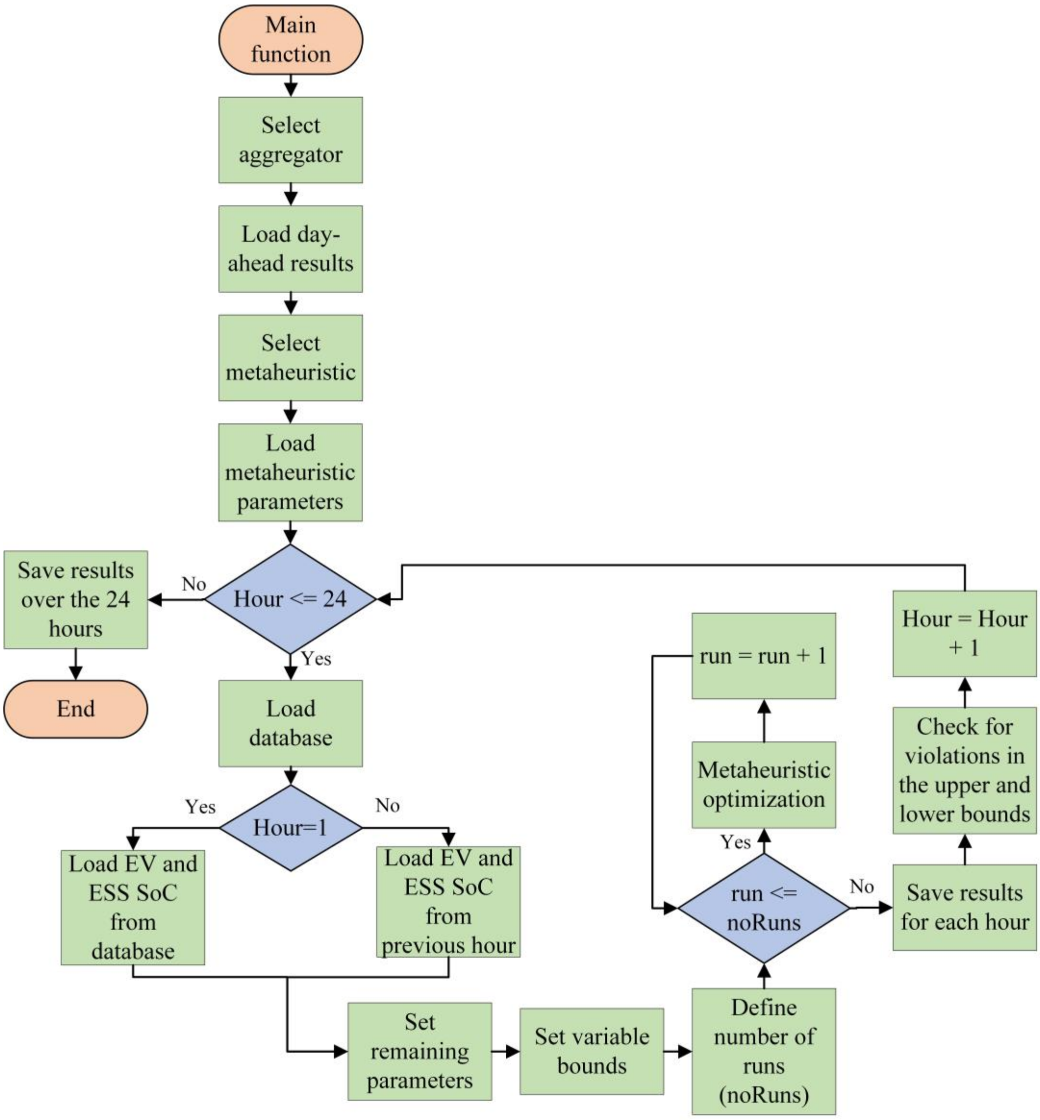


Figure 17 Flowchart of the main function of the proposed optimization technique.

Through a function, these results are saved, and the values of the external supplier, dispatchable generation, and WS market are fixed and assigned to the limits of these variables in intraday. Next, the metaheuristic to be used in the optimization process is selected, and the parameters associated with the algorithm are loaded accordingly.

The program then enters a cycle where it runs through each optimization hour, where the database is loaded. This database has the energy resources associated with the chosen aggregator in 15-minute time periods, four periods per hour.

For the SoC of the ESSs and the batteries of the EVs, a condition is created that will test if the optimization is running for the first hour. If this situation is verified, the initial state of these batteries is given by the values in the database. If the opposite happens, the initial state is provided by the SoC at the end of the previous hour.

The remaining parameters such as the ids of the different technologies, the number of scenarios to be evaluated in the fitness, and others are defined. Minimum and maximum limits are defined below for the variables in question. The number of runs for which you want to run the optimization is the next parameter to be set.

The optimization of the energy resources using the chosen metaheuristic is done by the program for the chosen number of runs, where at the end of all the runs the results for each hour are saved and a check of the solution according to the specified limits is also done, i.e., it is checked if the solution is a feasible solution. At the end of the program when the optimization done for each hour is finished the results over the 24 hours are saved to be compared with the day-ahead values.

3.3.2. ENCODING OF INDIVIDUALS

An essential aspect of the metaheuristics to express a given solution is the solution structure (e.g., an individual in DE, a particle in PSO, or a genotype in GA). In this case, since one is dealing with EAs, the solution of the metaheuristics in question is defined by the number of individuals.

The initial solution generated by the metaheuristic is initialized randomly between the maximum and minimum limits specified for each variable. Figure 18 shows the vector representation of the developed solutions for the hour-ahead.

Each solution per individual is represented by sequentially repeating a group of variables for all periods of the optimization hour, in this case, four periods (15 minutes each). All variables in this group are of the continuous type except for the binary variables associated with the state of the generators. This state is 0 if it is not connected to the grid and 1 if it is. For the intraday case, the dispatchable DG and WS market do not vary, and their bounds are equal to the values obtained in day-ahead, as stated earlier. The metaheuristics do not consider binary market variables because a condition is made with the buy and sell values in WS and LEM. If the markets have buy and sell values in the same period, the difference of the sale with the purchase is made. If this difference is negative, the selling value is set to zero, and the value of this difference is assigned to the buying value and vice versa. This formulation also guarantees the non-simultaneity condition.

In the group of variables belonging to the non-dispatchable generation that includes PV and wind generation, it is essential to note that this generation cannot be controlled; hence even if it is included in the vector solution, the variables relating to renewable generation will have a specific, and thus unchangeable, the value depending on the scenario.

Individual 1	D1	D2	D3	D4
Individual 2	D1	D2	D3	D4
Individual 3	D1	D2	D3	D4
...	...	...	...	
Individual NP	$\boxed{\text{D1}}$	D2	D3	D4

Group of variables		
Name	**Type**	**Bounds**
Dispatchable power generation	Continuous	[DApower]
Non-dispatchable power generation	Continuous	[minPower,maxPower]
Dispatchable power generation binaries	Binary	[DAbin]
Non-dispatchable power generation binaries	Binary	0,1
EVs charge/discharge	Continuous	[-maxDischarge,maxCharge]
Demand response	Continuous	[0,maxReduce]
ESSs charge/discharge	Continuous	[-maxDischarge,maxCharge]
WS market	Continuous	[DAbuy/sell]
LEM	Continuous	[-maxBuy,maxSell]

Figure 18 Representation of the generated solution for the intraday ERM model.

The number of variables is different depending on the chosen aggregator for the optimization. Table 3 presents the total number of variables each individual has for the day-ahead problem for each proposed aggregator, and Table 4 shows the number of variables for the hour-ahead problem. In this case, the first four aggregators have a small dimension when compared to the fifth aggregator. This situation results in a fast and better optimization process for the first four aggregators.

Table 3 Dimension of each individual for each aggregator in the day-ahead ERM.

Aggregator 1	*d*=24*19=456
Aggregator 2	*d*=24*31=744
Aggregator 3	*d*=24*23=552
Aggregator 4	*d*=24*47=1,128
Aggregator 5	*d*=24*2016=48,384

Table 4 Dimension of each individual for each aggregator in the intraday ERM.

Aggregator 1	*d*=4*20=80
Aggregator 2	*d*=4*32=128
Aggregator 3	*d*=4*24=96
Aggregator 4	*d*=4*48=192
Aggregator 5	*d*=4*2017=8,068

3.3.3. FITNESS FUNCTION

The methodology adopted for the fitness function is the same for the day-ahead and intraday models. The internal evaluation of the fitness of the scenarios is the different process between the two. The internal assessment adopts the formulations described in chapter 3.1. Figure 19 shows the general operation of the fitness function, which initially receives as inputs the array of solutions generated by the metaheuristics previously described in the subchapter 3.3.2. It also gets the information of the case study database for all simulated scenarios, some additional information, and the number of scenarios to be evaluated in the fitness.

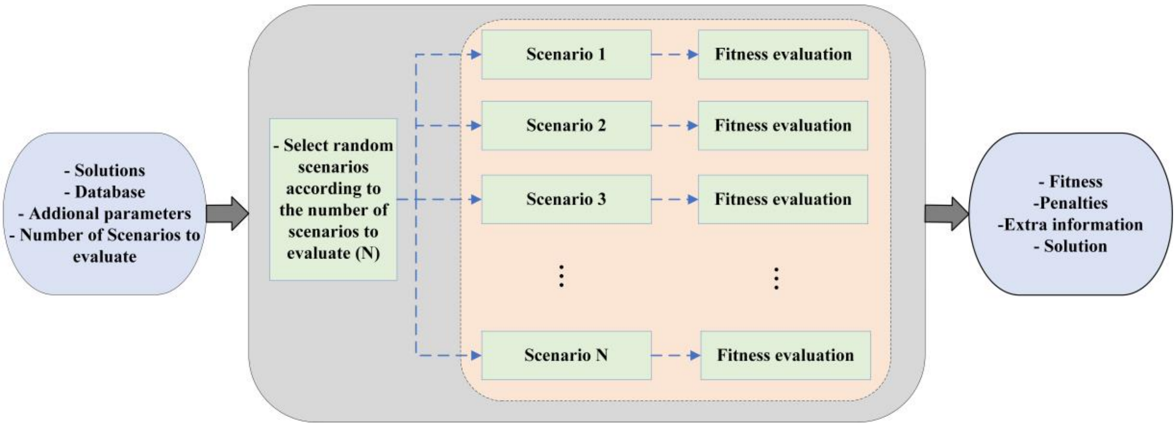


Figure 19 Fitness function structure of ERM model.

After providing the inputs for the fitness function, several random scenarios are selected from the total scenarios in the case study according to the number of scenarios to be evaluated. In this case, a number of 10 random scenarios are internally assessed in the fitness both for the day-ahead and hour-ahead models. When it comes to the risk-based strategy, all scenarios in the database are evaluated.

A maximum number of objective function evaluations is also set. This number depends on the number of scenarios evaluated and the number of solutions as well.

Regarding the optimization process of the risk-based methodology Figure 20 shows the fitness function that the chosen metaheuristic evaluates for cost minimization. Initially the database with the formulated scenarios is passed as argument to the function, and the value of the variable that controls risk aversion is also initialized. Next, each scenario is evaluated according to the equations in Section 3.1. This evaluation is done in order to obtain the cost of each scenario, which is saved to then calculate the expected cost.

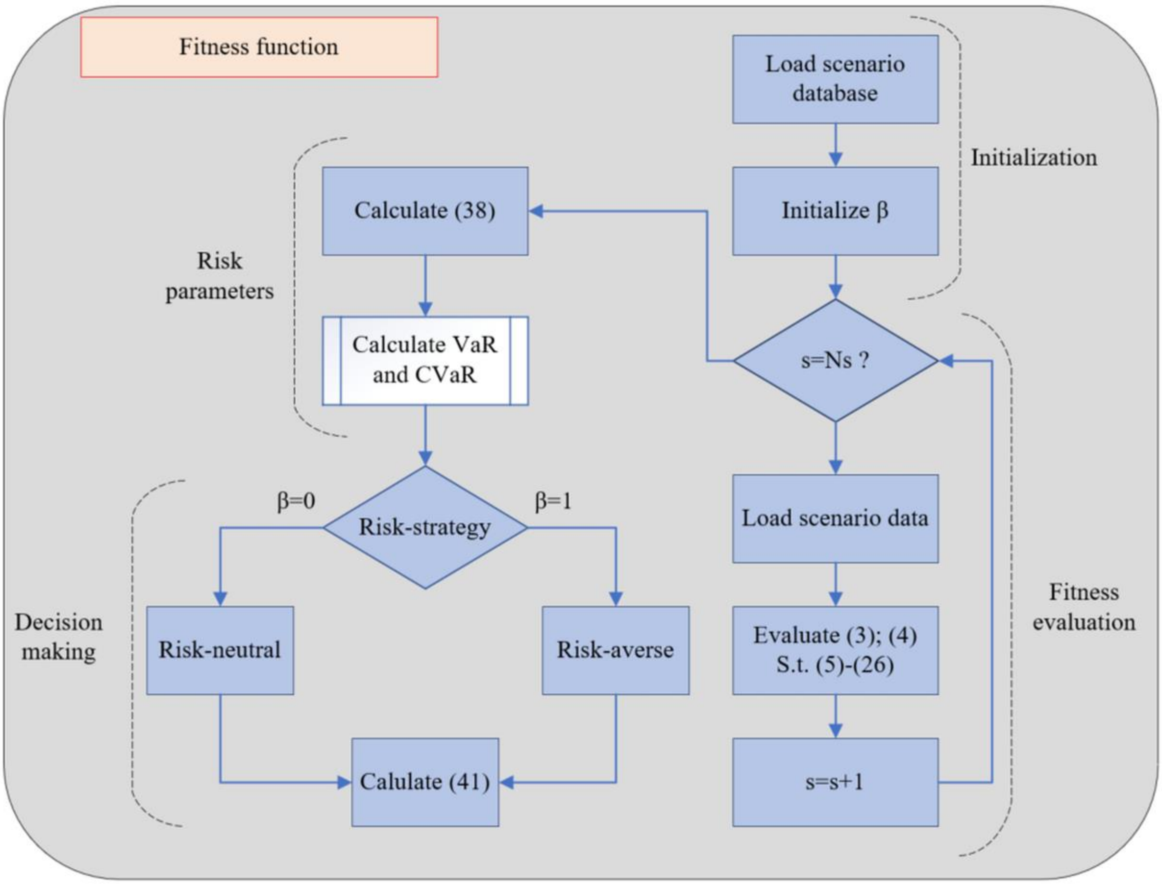


Figure 20 Fitness function of the risk-based optimization.

The expected cost, the cost of each scenario, and the probabilities of each scenario are used to calculate the VaR_{α} and $CVaR_{\alpha}$ values according to the formulation in Section 3.2. After the parameters that measure risk have been calculated, the aggregator enters a decision process according to the risk aversion factor. That is, through the value of the OF the aggregator chooses the best strategy.

This evaluation is done by the metaheuristic in order to minimize the value of the OF in a given number of iterations, so when the beta is zero the metaheuristic will only minimize the expected cost, but when the beta is 1 the metaheuristic tries to minimize the expected cost as well as the $CVaR_{\alpha}$.

3.4. UNCERTAINTY

The aggregators in the considered model experience uncertainty originating from multiple resources (random driving patterns of EV users and charging behavior) through projected uncertainties of market prices, renewables, and EV travel behavior. Due to the randomness of these variables, the outcome is nearly impossible or impossible to determine, so the decision-making process cannot be done correctly. These uncertainties associated with the mentioned resources are considered in the proposed method through a scenario-based optimization technique. The Monte Carlo Simulation (MCS) method is used, which will obtain numerical results using massive random sampling; that is, it will repeat subsequent simulations many times to calculate the heuristic probability [79]. For any variable with uncertainty, it creates a viable product model using a probability distribution, in this case the normal distribution function. The findings are then recalculated using a range of values between the minimum and maximum. The scenarios x^{s} can be represented as the sum of the errors obtained from historical data as given by:

$$x^{s} = x^{forecasted}(t) + x^{error,s}(t). \tag{42}$$

Where $x^{forecasted}(t)$ is the error related to the forecast made in each instant t, which can have a negative or positive value, $x^{error,s}(t)$ is the term associated with the error involving each scenario s with a normal distribution function with a zero-mean noise, and standard deviation σ.

Figure 21 shows an example of a scenario tree where each circle represents a node which gives the state of a random variable at a certain time, and each branch represents the specific scenario.

Many scenarios are initially created resulting in a large-scale problem. The larger the number of scenarios is the more accurate the model is. Despite the great accuracy that can be obtained there is a tradeoff in terms of computational time and memory requirements. The larger the set of scenarios is the more time and memory is required. To handle tractability of the problem, a scenario reduction technique is used [80]. Similar scenarios are bundled together, and scenarios with a low probability of occurrence are eliminated. A scenario subset is then created close to the initial distribution in terms of a probability metric. The primary goal of scenario reduction is to make the large-scale problem substantially smaller. After using these methods, the number of variables and constraints is reduced. As a result, the computational time is significantly reduced, finding reasonable solutions quickly while maintaining the primary statistical characteristics of the original dataset. The computational effort is also reduced, and less system memory is required, but accuracy is reduced due to imprecisions introduced to the final solution.

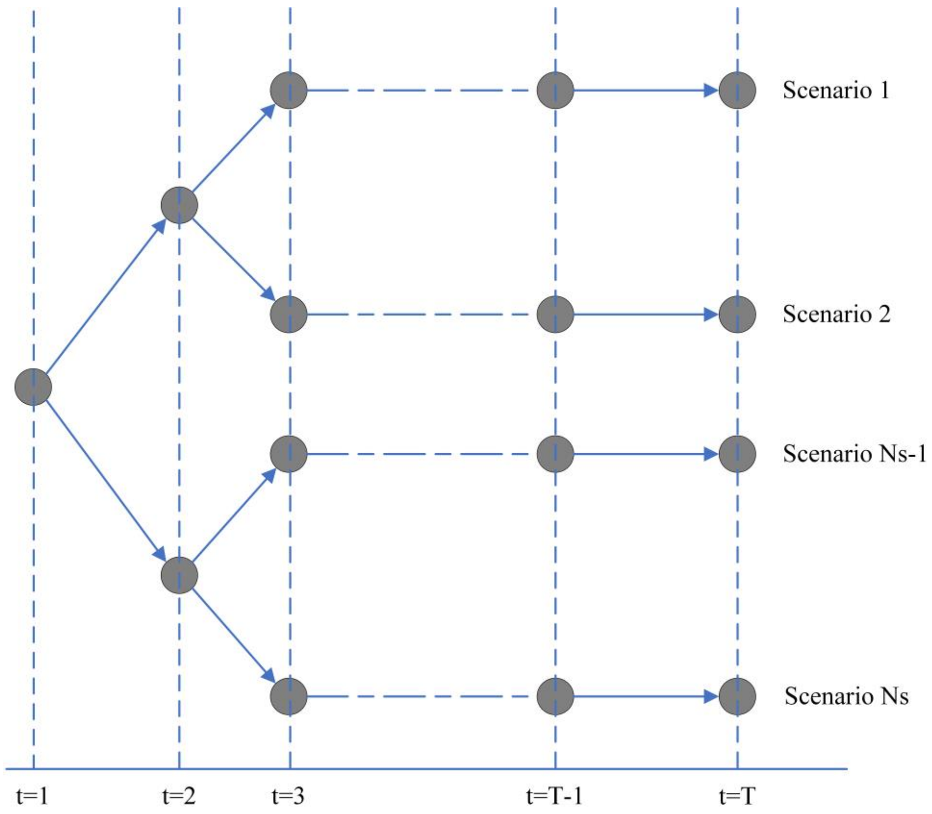


Figure 21 Scenario tree.

In the intraday methodology, the scenario with the highest probability was sought in the scenarios created for the day-ahead to generate scenarios to address the uncertainty in the intraday time horizon. This scenario served as a base for creating the new scenarios applying a small noise variation to the parameters with uncertainty through the normal probability distribution function $\mathcal{N}(1{,}0.05)$ with a mean value of one and standard deviation of 5%. For each created scenario it was assumed that the probability should be equal given by $\frac{1}{N_s}$. This method is not the most correct when creating new scenarios, and a methodology similar to the one applied to the creation of scenarios for the day-ahead should be implemented in the intraday model.

Regarding the risk-based strategy, ten random extreme scenarios from the database were created, simulating realistic situations for extreme events. This number of scenarios was chosen in order to try to guarantee a balance between the occurrence of extreme events and normal scenarios, thinking about what events with low probability of occurrence could be, but with great impact on the solution, for the operation problem, since this is a methodology not present in the literature for this type of problem.

In the first extreme scenario modeled a 50% increase in load during the day was considered. Regarding the second extreme scenario created a reduction of 80% in market capacity of buy/sell was considered all day. Damage to the distribution lines can cause a significant reduction in the maximum power capacity that the external supplier can supply, so in the third extreme scenario generated the external supplier maximum generation limit was reduced to 8 MW in hours 1 to 7 and 23 to 24. The inexistence of DR that can be caused by the failure of the communication system between aggregator and end-user was considered in the following scenario were the DR was set to zero all day, and an increase of 40% in demand was considered in hours 16 to 22. The following scenario that can cause risk to the aggregator considered a 60% of load increase, a 20% rise in wind generation in different parts of the day, and a 30% PV production increase. In the sixth extreme scenario created a 30% load increase from hours 13 to 20 was modeled and the inexistence of market capacity for trading occurred from hours 1 to 12 and 22 to 24. In the following scenario the external supplier capacity was again limited, and a rise in market prices also occurred in different hours. A market capacity of 4 MW, and a 30% increase in renewable generation were considered in the next created scenario. A load increase of 50%, a DR capacity reduction of 30%, and a rise of 80% in market prices were considered during multiple parts of the day in the extreme scenario number nine. The final scenario of risk modeled contemplated an increase of 120% in electricity market prices that occurred during the 17th hour to the 22nd hour of the day, and a 60% DR reduction from hour 9 to hour 19.

The total probability of the extreme scenarios was equal to 0.5%. Since the extreme events have a low probability of occurrence, i.e., these scenarios were given a lower probability than the lowest probability existing in the database. In this case, the probability of the remaining scenarios needed to be altered so the total could be equal to 100%. The normal scenarios in the database were added an equal probability given by:

$$S_{s-r} = \frac{1 - \sum_{s=1}^{N_s} \rho_s}{N_s - N_r}. \tag{43}$$

Where S_{s-r} represents the probability added to the normal scenarios, and N_r is the total number of extreme scenarios.

3.5. CHAPTER CONCLUSIONS

In this chapter, the ERM models for day-ahead and hour-ahead were presented, and their mathematical formulations considering cost and profit functions that are subject to several constraints. A risk strategy for day-ahead scheduling was also formulated, considering VaR and CVaR as risk measurement tools. An entire optimization technique underlies the proposed models. The general structure of the program used in intraday is shown, how the population generation is done by the metaheuristics, and the problem dimension of each proposed aggregator for the day-ahead and hour-ahead time horizons. Once the population is generated, it is necessary to evaluate each individual through a fitness function. The fitness function evaluation methodology is then presented for the ERM case for the multiple aggregators and the risk aversion strategy. To deal with the uncertainty of the energy resources considered here, the modulation for the generation of scenarios is presented through an MCS for day-ahead scheduling. Through this simulation, many scenarios that resulted from that to alleviate computational requirements were reduced. From this reduction, the scenario with the highest probability was chosen to generate new scenarios for intraday, with a variation associated with them. Also, in the scenario generation was presented, in this case manually, the generation of scenarios corresponding to extreme events for the risk-based optimization. All this methodology will be applied to the case study presented in the next chapter (chapter 4).

4. CASE STUDY

The proposed methodology previously shown is applied to the case study described in this section.

4.1. DISTRIBUTION NETWORK AND EV SCENARIO SIMULATOR

This case study considres five different aggregators [81]. Each aggregator is responsible for managing a variety of resources, including those that are incorporated into a 13-bus DN inserted in a smart city (SC) in the BISITE laboratory in Salamanca, Spain (mock-up), with a variety of loads, a high percentage of EVs, and renewables like Figure 22 shows [82].

This DN is composed by 25 load points of multiple types, namely: 1375 homes; 7 office buildings; 1 hospital; 1 fire station; 1 shopping mall. It features one 30MVA substation located at bus 1, 15 DG units (2 wind farms and 13 PV parks), and four 1Mvar capacitor banks.

The SC in question has seven charging stations allowing a large number of EVs to charge their batteries, including four 7.2kW slow charging stations per connection point and 50kW fast charging stations per connection point. Figure 23 shows all of the technologies listed as a single-line diagram of the 13-bus.

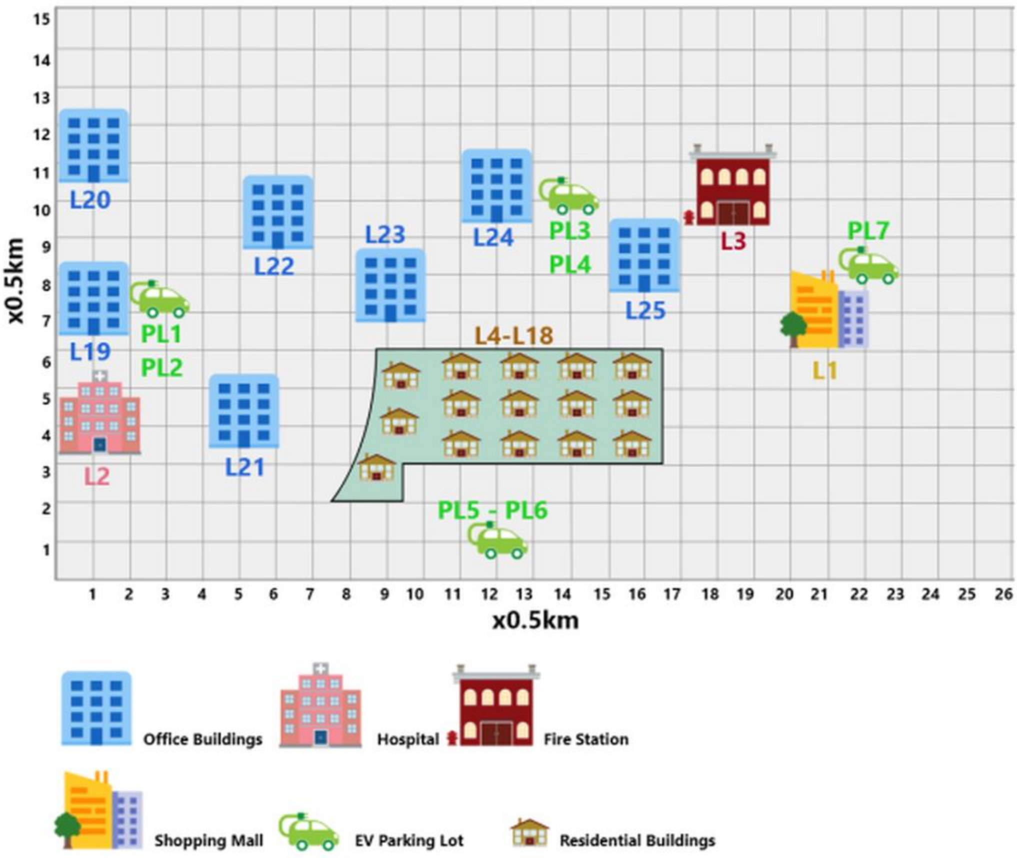


Figure 22 Smart city schematic [82].

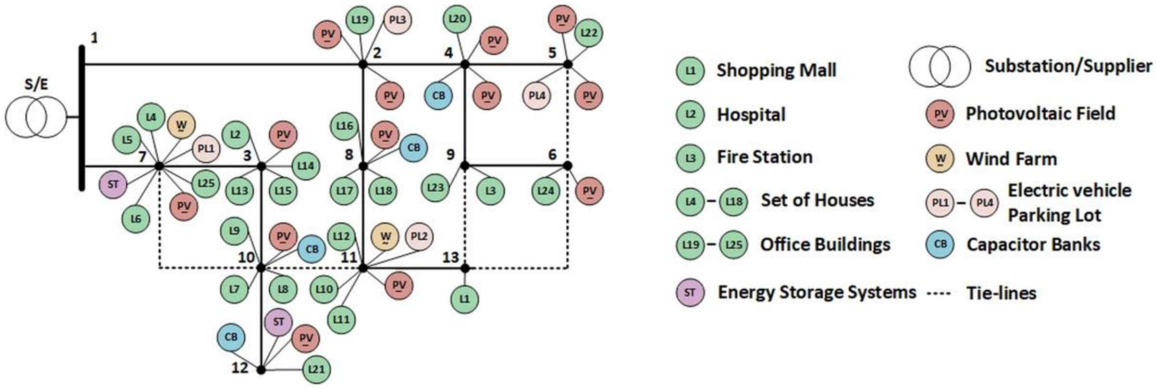


Figure 23 Single-line diagram of the distribution network [82].

The considered aggregators are divided as follows:

- Aggregator 1: Service loads (hospital, fire station, and shopping mall);
- Aggregator 2: Residential loads;
- Aggregator 3: Office loads;

- Aggregator 4: Renewable production;

- Aggregator 5: Evs.

For the performed simulations a total of 2000 Evs were considered where the data from each was obtained from an EV Scenario Simulator Tool available in [83]. The software receives as inputs the initial SoC of the batteries, a step rate, the total number of periods, the maximum allowed discharge percentage, charging and battery efficiency, and the total number of EVs considered. Other parameters are considered for the simulator as shown in Table 5 such as the percentage of cars in charging as well as the percentage of cars that are inside the network, which in this case were considered 100%, i.e., no cars leave or enter the considered DN. A period and distance distribution are also used as inputs where the trip distance distribution is comprehended between 10 and 190 km.

Table 6 lists the types of EVs for the six vehicle model types (four BEVs and two PHEVs) used in this simulator. According to [84], this table also shows the vehicle class and their associated description.

Table 5 Inputs for the Electric vehicle Trip Simulator [83].

Parameter	Description	Value
initialStateOfBats	Initial state of batteries	30%
stepRate	Simulation time step	1 hour
totalStep	Total number of steps (periods)	24
batteryMaxDoD	Battery max. depth of discharge permitted (DoD)	80%
chargerEfficiency	Charging device efficiency	88%
batteryEfficiency	Battery efficiency	90%
evNum	Number of electric vehicles	2000
sameInitalEndBusProb	Probability of the EV to end in the same starting network bus in the simulation scenario	100%
parkedAllDay	Cars percentage that are always parked and connected to the grid	5%
carsInsideNetwork	Cars percentage that remain inside distribution network	100%
carsGoingOutsideNetwork	Cars percentage that leave distribution network	0%
carsGoingInsideNetwork	Cars percentage that arrive from other distribution network	0%

Table 6 Electric vehicle model description.

Model ID	Vehicle type	Vehicle class	Description
1	BEV	L7e	Passenger car
2	BEV	M1	Passenger car
3	BEV	N1	Commercial van
4	BEV	N2	Light truck
5	PHEV	M1	Passenger car
6	PHEV	N1	Commercial van

Table 7 presents the characteristics associated with each EV considered when it comes to battery capacity, charging rate for slow and fast charging stations, the energy consumption, average usage and speed, and tank capacity when the EV is the PHEV type, since it also has in its engineering a combustion engine.

Table 7 Electric vehicle model characteristics.

Model ID	Battery capacity (kWh)	Slow charging rate (kW)	Fast charging rate (kW)	Average economy (kWh/km)	Average speed (km/h)	Average usage (km/day)	Tank capacity (liters)
1	6.10	3.60	0.00	0.06	20.00	30.00	0.00
2	40.00	6.60	50.00	0.16	38.00	34.00	0.00
3	33.00	7.40	0.00	0.19	56.00	32.00	0.00
4	82.80	7.20	50.00	0.65	136.00	16.00	0.00
5	8.90	3.30	0.00	0.11	20.00	16.00	43.00
6	13.60	3.70	0.00	0.26	20.00	16.00	54.00

Table 8 shows the distribution percentage of each class, which means that from the 2000 EVs, 10 are Le7 cars, 1740 are M1 cars, 200 are N1 vehicles, and 50 are N2 vehicles. For the BEVs, a 67% distribution was considered and 33% for PHEVs. This simulator allows to obtain data regarding each EV's trips such as maximum charge, and discharge rate, minimum charging required so the EV can make its trip in the next hour, and many other parameters that serve as input for the optimization.

When all these inputs are entered into the tool, it will give as outputs the total number of kilometers driven by each simulated vehicle, the energy expended by the battery per trip, the number of trips made, and the total energy expended by the battery in the total number of trips.

Table 8 EV classes distribution.

Vehicle class	Share (%)
L7e	0.50
M1	87.00
M2	0.00
M3	0.00
N1	10.00
N2	2.50
N3	0.00

4.2. ENERGY RESOURCE INFORMATION

Five thousand scenarios were generated concerning load consumption, renewable production, electricity market prices, and EV charging stations in the day-ahead scheduling. The highest standard deviation values for the uncertainty variables evaluated (load consumption, electricity market price, parking lot capacities, parking lot charge, and discharge) are 15%, 10%, 35%, 35%, and 35%, respectively. Minimum values are 8%, 6%, 20%, 20%, and 20%. The standard deviation (or error) between these bounds for these parameters is calculated using random values. The charging station discharge term was not considered in the objective function. Instead, the EV discharging term was considered. Figure 24 depicts the average of the precise standard deviation (percentage) for the forecast of the renewable technologies, in this case, study (wind and PV) for the day-ahead time horizon [85].

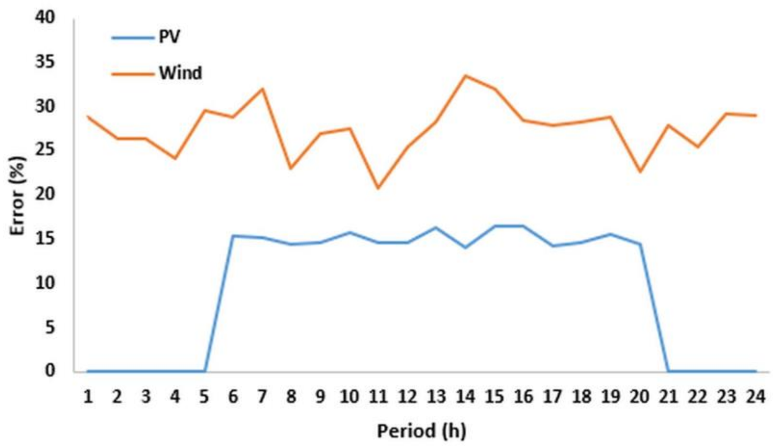


Figure 24 Average forecast error for generation technologies [85].

Each aggregator must manage their respective resources, power bought from the external supplier, and energy bought/sold in the marketplaces. Two ESSs were also considered and are attributed to all aggregators. Also are integrated into the DN four capacitors but are not considered in this problem, so they are set to zero because reactive power was not taken into consideration in the problem formulation. Table 9 presents the data of the energy resources associated with each aggregator for the day-ahead formulation where a distinction is made from the aggregators, prices of the resources, capacity, forecasted values from the renewables and loads, and the number of units corresponding to each resource. In this case study, the costs of PV and Wind are much higher than the costs of the other technologies because they are levelized costs taken from [86], where the costs of the installations throughout their useful life are also included [87].

Table 9 Energy resources information of each aggregator in the day-ahead model.

Energy resources		**Aggregators**	**Prices (m.u./MWh)**	**Capacity (MW)**	**Forecast (MW)**	**Units**
			min-max	**min-max**	**min-max**	
Capacitors		1-5	0-0	0.00-0.00		4
Photovoltaic		4	150-150		0.00-0.81	13
Wind		4	130-130		0.00-3.75	2
External supplier		1-5	50-90	0-30.00		1
Storage	Charge	1-5	110-110	0.00-1.25		2
	Discharge		90-90	0.00-1.25		
Electric vehicles	Charge	5	0-0	0.01-0.13		2000
	Discharge		90-90	0.01-0.09		
Demand response	Reduce program 1	1	100-100	0.01-1.21		3
	Reduce program 2	2	100-100	0.01-0.08		15
	Reduce program 3	3	100-100	0.28-1.11		7
Load type 1		1	0-0		0.01-2.25	3
Load type 2		2	0-0		0.01-0.14	15
Load type 3		3	0-0		0.31-1.91	7
Market buy and sell		1-5	27.99-65.97	0.00-10.00		1

In the intraday, 150 new scenarios were produced from the scenario with the highest probability in the day-ahead. A normal distribution function was applied to the uncertain resources from this scenario with a 5% variation to inject into the provided hour-ahead model using these generated scenarios. This circumstance is not ideal, and it may cause a minor change in the obtained results because the same technique applied in the day-ahead model should be applied for the hour-ahead making the forecast no for 24 hours but for 96 periods of 15 minutes each.

The overall demand and renewable generation forecasted by the proposed method for the first four aggregators is shown in Figure 25. From aggregator 1 to 3, the range for the total demand is given, and full renewable power is demonstrated in aggregator 4.

Figure 26 demonstrates the prices in intraday marketplaces for these aggregators' resource optimization when it comes to the external supplier, WS electricity market, and the proposed LEM.

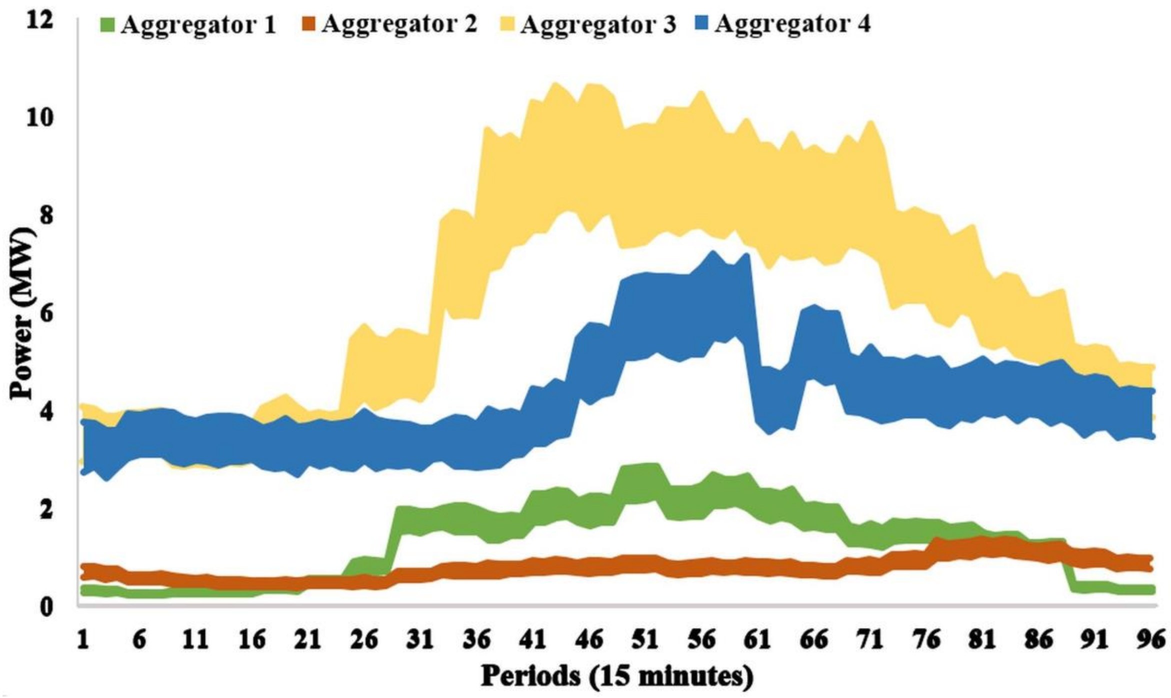


Figure 25 Total demand and renewable generation forecast for each aggregator in the intraday time horizon.

Compared to the LEM, which changes the prices in the range depicted in Figure 26 the external supplier and WS market prices are fixed and do not alter because the contracts from the power bought from the external supplier and the WS market were closed in the day-ahead scheduling. Because the LEM is often more expensive than the WS market due to its proximity to the retail market, the price gap between the two markets was calculated at 25%

with the prices of the LEM suffering a 5% variation. The considered percentage was small because it turned out that the higher this percentage is, the more the algorithm will try to sell the excess in the market to earn a higher profit which often caused a decrease in costs from day-ahead to intraday, which is not expected to happen because the scheduling gets closer to real-time which corresponds to an increase in costs from the day-ahead. The LEM is regarded to have 25% the capacity of the WS market because this market exists in a neighborhood environment, i.e., with a small capacity compared to the WS market, and prices closer to retail [3].

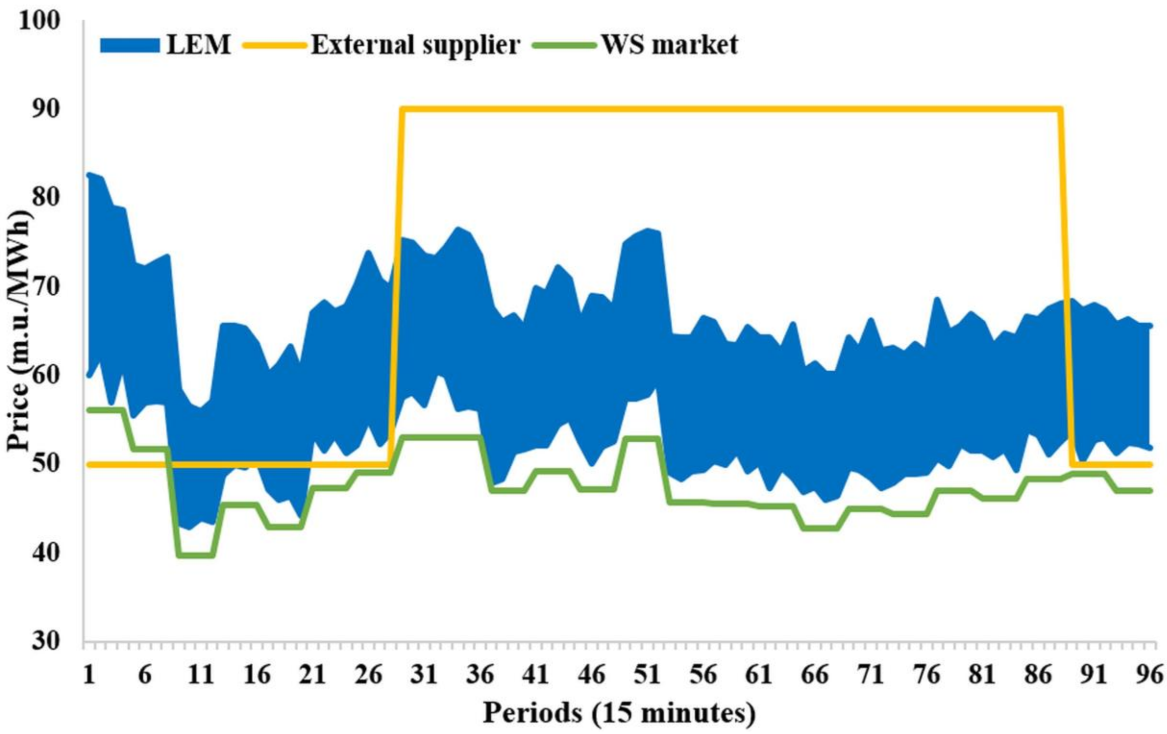


Figure 26 External supplier, WS market, and LEM prices for the intraday time horizon.

Table 10 presents the data of the energy resources associated with each aggregator for the intraday time horizon. The values presented correspond to each resource between all the units and not to the total values like the figures previously shown demonstrate. In this case most of prices remain the same as they were in the day-ahead model shown in Table 8 with the difference being the WS market prices that now are fixed and the introduction of the LEM prices. The forecasted values are also altered due to the time horizon being different.

Table 10 Energy resources information of each aggregator in the intraday model.

Energy resources		Aggregators	Prices (m.u./MWh) min-max	Capacity (MW) min-max	Forecast (MW) min-max	Units
Capacitors		1-5	0-0	0.00-0.00		4
Photovoltaic		4	150-150		0.00-0.94	13
Wind		4	130-130		0.60-2.80	2
External supplier		1-5	40-90	0-30.00		1
Storage	Charge	1-5	110-110	0.00-1.25		2
	Discharge		90-90	0.00-1.25		
Electric vehicles	Charge	5	0-0	0.01-0.13		2000
	Discharge		90-90	0.01-0.09		
Demand response	Reduce program 1	1	100-100	0.01-1.21		3
	Reduce program 2	2	100-100	0.01-0.08		15
	Reduce program 3	3	100-100	0.28-1.11		7
Load type 1		1	0-0		0.01-2.23	3
Load type 2		2	0-0		0.01-0.13	15
Load type 3		3	0-0		0.31-1.88	7
Market buy and sell		1-5	39.66-56.08	0.00-10.00		1
Local electricity market buy and sell		1-5	42.97-82.61	0.00-2.50		1

4.3. RISK-BASED ENERGY RESOURCE INFORMATION

In the risk-based formulation for some extreme scenarios, a large variation is noticed from the variable inputs of the aggregator. In this case, variations in load demand and renewable generation are seen. Figure 27 presents the total load demand and renewable generation varying between the minimum and maximum values for a total of 24 hours.

It is possible to observe that a significant difference between load limits is verified from approximately hours 10 to 20. When it comes to renewable generation variations, the proposed extreme scenarios did not essentially influence the minimum and maximum limits because the presented range is diminutive compared to the load demand. Regarding the considered costs in this scenario Figure 28 presents the range of the WS market prices and the external supplier prices. A significant variation can be seen regarding the market prices due to the multiple extreme scenarios that consider an increase in market costs. Here the maximum value increases from 65.97 m.u. to 116.22 m.u. (hour 21) an increase of 43.24% from what was considered in Section 4.2, with the external supplier costs remaining the same.

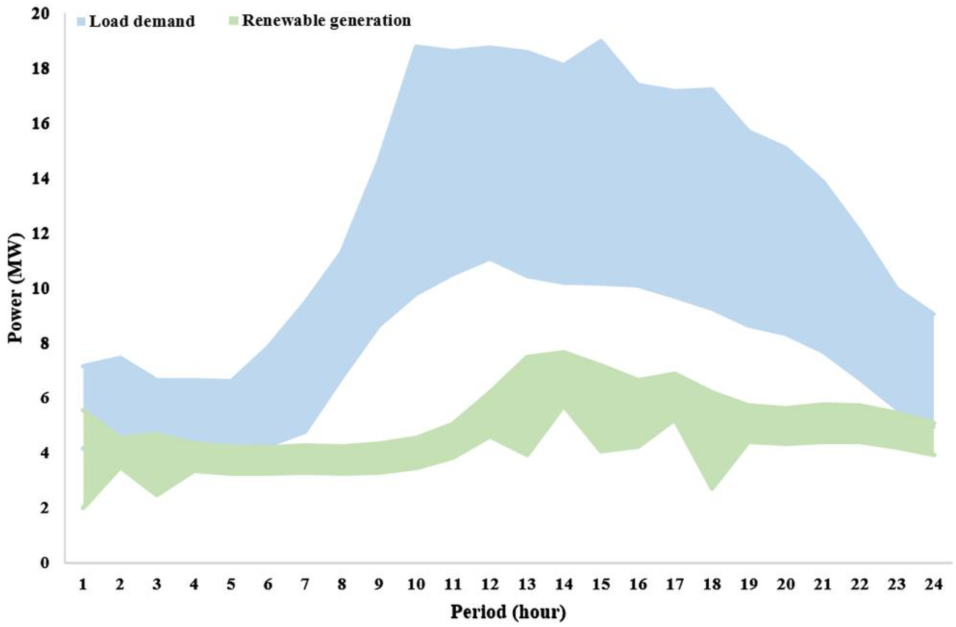


Figure 27 Load demand, and non-dispatchable generation for risk-based model.

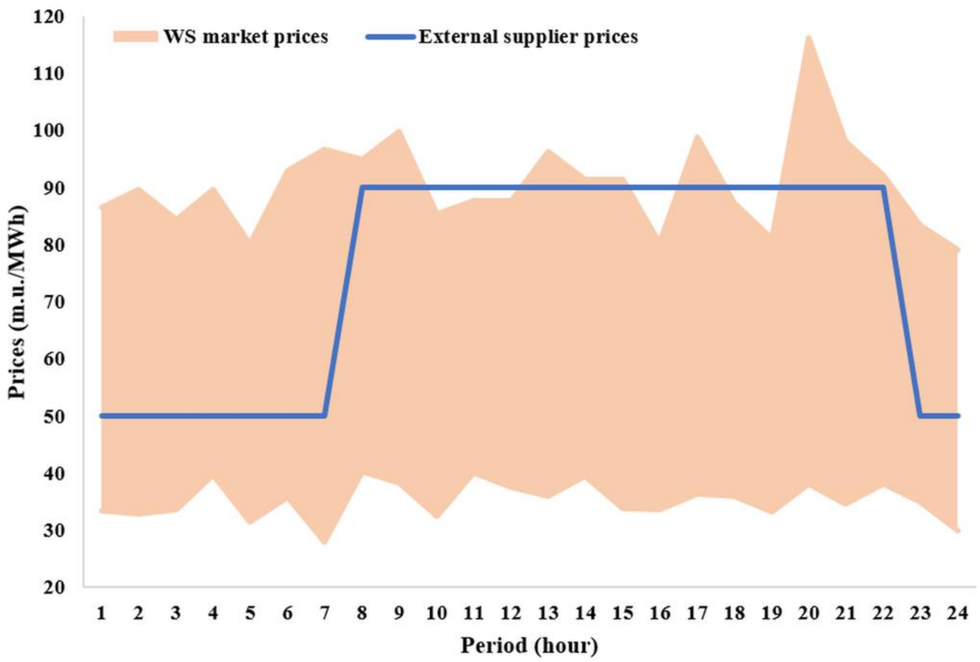


Figure 28 External supplier, and WS market prices for risk-based model.

Note that if (6)-(10), (12)-(13), (17)-(18), and (21)-(25) are violated a penalty of 1,000 m.u. is added to P_S in (37) for each variable that exceeded the specified bounds.

4.4. ALGORITHM PARAMETERS

Multiple metaheuristics were used to solve the proposed energy management model for the day-ahead and intraday models, and Table 11 shows the parameters chosen for each algorithm. For all metaheuristics, the population size (NP) and the maximum number of iterations was 20, and 250 respectively, taking into consideration the number of objective function evaluations set to 50,000 considering the number of evaluation scenarios which was set to 10 to reduce computational effort and time taken by the heuristics. When it comes to the risk-based approach since the total of scenarios to be evaluated is 150, and maintaining the NP, and the maximum number of iterations, the objective function evaluations was set to 750,000.

The sensibility of the NP parameter was studied in [85] for the day-ahead and it was concluded that the overall best value for this parameter in the tested metaheuristics was 20. The crossover probability (Cr) and scaling factor (F) are the following parameters, which are necessary for the first three displayed algorithms. The sub-population size is given by p, and the number of selected individuals is provided by s. α represents the additional occurrence used in the scaling method of the HC2RCEDUMDA algorithm. The number of elitist individuals is represented by l. The neighborhood ratio is given by r. Finally, k is the number of codes used in the HC2RCEDUMDA metaheuristic.

A statistical ranked test was also applied to these metaheuristics for a comparison of performance. A Wilcoxon test was chosen to test the algorithms where a base metaheuristic served for comparison, in this case the CUMDANCauchy++ which obtained great results in the *"2020 Competition on Evolutionary Computation in the Energy Domain: Smart Grid Applications"* which incorporated an ERM problem similar to the one proposed.

All performed simulations were run in MATLAB 2018a with Windows 10 using a machine with a quad-core AMD Ryzen 5 3500U processor with 2.1 GHz base clock speed and 16GB of RAM.

Table 11 EAs parameters.

<table>
<tr><th>Parameter</th><th>DE</th><th>HyDE-DF</th><th>DEEDA</th><th>CUMDANCauchy++</th><th>HC2RCEDUMDA</th></tr>
<tr><td>NP</td><td colspan="5">20</td></tr>
<tr><td>Max iterations</td><td colspan="5">250</td></tr>
<tr><td>Cr</td><td colspan="3">0.5</td><td colspan="2">-</td></tr>
<tr><td>F</td><td colspan="3">0.3</td><td colspan="2">-</td></tr>
<tr><td>p</td><td colspan="2">-</td><td>16</td><td>16</td><td>-</td></tr>
<tr><td>s</td><td colspan="2">-</td><td>2</td><td>2</td><td>3</td></tr>
<tr><td>α</td><td colspan="4">-</td><td>0.009</td></tr>
<tr><td>l</td><td colspan="4">-</td><td>3</td></tr>
<tr><td>r</td><td colspan="4">-</td><td>3</td></tr>
<tr><td>k</td><td colspan="4">-</td><td>7</td></tr>
</table>

4.5. Chapter conclusions

In this chapter, the case study for the application of the developed methods is presented. Since multiple aggregators are considered in the DN given here, their aggregated energy resource division is done. To generate the data for the EV aggregator, a scenario generation tool was used for the trips of each electric vehicle. In this case, high penetration of cars (2000 EVs) is considered. This tool allows obtaining the uncertainty parameters considering the characteristics of each car considered and multiple probabilistic distributions as demonstrated. The variation of uncertain resources for day-ahead and intraday and the risk methodology is presented. Due to the risk scenarios created, the latter shows a more significant variation in the aggregator inputs. Since multiple metaheuristics are used to optimize resource scheduling, the definition of their parameters is presented here. These parameters are chosen because in [85], a sensitivity analysis of the number of individuals and the number of iterations was done, keeping the same number of objective function evaluations.

5. RESULTS AND DISCUSSION

This section presents and discusses the results obtained for the intraday ERM problem when multiple metaheuristics are applied. The results for the risk-based mechanism applied to the day-ahead problem considering only one aggregator in the DN are also presented.

5.1. DAY-AHEAD AND INTRADAY SCHEDULING RESULTS

The best-obtained results (lowest cost) for the day-ahead problem for one run using CI is presented in Table 12. In [85] with CUMDAN obtained the best scheduling results for the day-ahead but for this case with different external supplier costs, and EV charging/discharging costs HyDE-DF presented better results in comparison to this algorithm, so Table 12 presents the day-ahead results for the HyDE-DF algorithm. It shows each proposed aggregator's cost when scheduling their resources for the next 24 hours. The time that the program took to complete the run is also presented in Table 12. It is possible to observe that the last aggregator was the slowest to optimize due to the number of variables which is significant more when compared to the other aggregators as seen in Section 3.3.2.

Table 12 Day-ahead objective function results and optimization time.

Aggs	Costs (m.u.)	Penalties (m.u.)	Time (s)
1	1,508.84	0.00	12.30
2	985.62	0.00	13.43
3	7,793.99	0.00	14.92
4	8,641.38	0.00	12.35
5	906.80	0.00	392.71

The day-ahead scheduling results for the first aggregator are presented in Figure 29. The total energy generated/consumed was 29.73 MWh with 29.31 MWh being load, 0.31 MWh being ESS charging, and 0.11MWh being from market sales from the consumption side. From the generation side 0.24 MWh is given from the external supplier (DG type 2), 1.77MWh from the DR, 0.23 MWh from ESS discharging and finally 27.49 MWh from market buys.

It is possible to observe from Figure 29 that the consumption is majorly given by the demand from the loads associated with the aggregator. When it comes to power generation the aggregator majorly goes to the WS market to buy energy with some DR, and ESS discharge. In period 5 the aggregator chooses to buy from the external supplier because he considers that it is cheaper to buy from the external supplier in relation to the market as seen in the remaining periods.

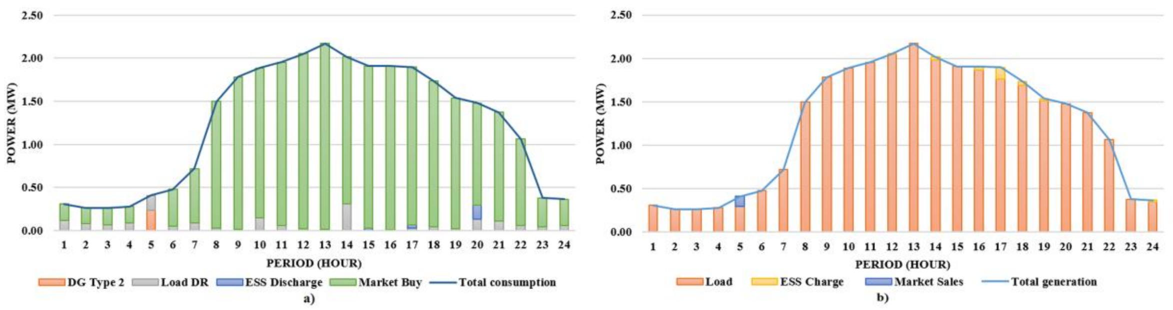


Figure 29 Day-ahead scheduling results for aggregator 1 regarding power a) generation; b) consumption.

When it comes to the second aggregator the scheduling results are given in Figure 30. The total energy generated/consumed was 21.14 MWh. In the consumption 5.12 MWh is given by the residential loads, 0.22 MWh by ESS charging, and 1.96 MWh from WS market sales. The total generation is obtained from 5.12 MWh of external supplier generation, 1.03 MWh from DR, 0.16 MWh from the discharging of ESSs, and 14.83MWh of WS market buys. Here it is worth noticing that the aggregator in some periods, mainly in periods 4, 6, and 24, decides to get energy from the external supplier when it is cheaper and sells the excess in the market to make some profit (Figure 26). In the remaining periods the aggregator buys energy in the market to satisfy the demand.

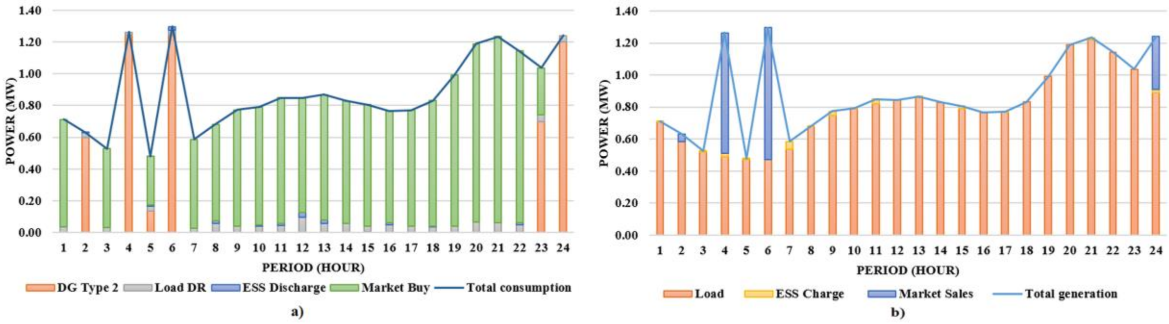


Figure 30 Day-ahead scheduling results for aggregator 2 regarding power a) generation; b) consumption.

The day-ahead scheduling results for the third load aggregator are demonstrated in Figure 31. The total energy generated/consumed was 151.26 MWh which is significantly higher compared to the previous aggregators, that is, their costs are also much higher compared to the costs of the other two load aggregators as shown in Table 12. Office loads account for 148.45 MWh of consumption, 1.50 MWh of ESS charging, and 1.61 MWh of WS market sales. 16.25 MWh of external supplier generation, 10.46 MWh of load reduction, 0.91 MWh of ESS discharging, and 123.94 MWh of WS market buys make up the entire generation. Once again, this aggregator mainly acquires energy to satisfy its demand. In the early periods it is seen that some energy is acquired from the external supplier as it pays off in some evaluated scenarios. However, most of the energy is purchased in the market. In the last period the aggregator sells the excess energy acquired through the DR and external supplier in the market to obtain some profit. Since the cost of the external supplier is low in the last period, the aggregator decides that it pays him to buy from the external supplier at a particular value and still sell to the market, something that does not happen in the other periods, where it only buys energy to satisfy the load.

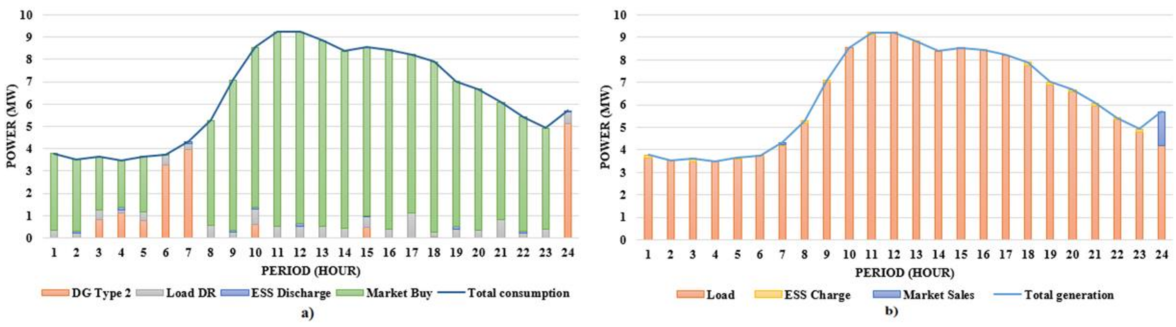


Figure 31 Day-ahead scheduling results for aggregator 3 regarding power a) generation; b) consumption.

The fourth aggregator is the renewable production aggregator, and its scheduling results are given by Figure 32. The energy generated/consumed was a total of 100.81 MWh with 100.45 MWh being from renewable generation (DG type 1), 0.16 MWh from the external supplier, and 0.21 MWh from ESS discharging energy. 100.39 MWh market sales are obtained, and 0.42 MWh of ESS charging is also presented in the consumption. In this case the aggregator sells all renewable energy in the market. Even though this situation occurs this aggregator presents the higher costs because the renewable energy costs are way higher than the market prices.

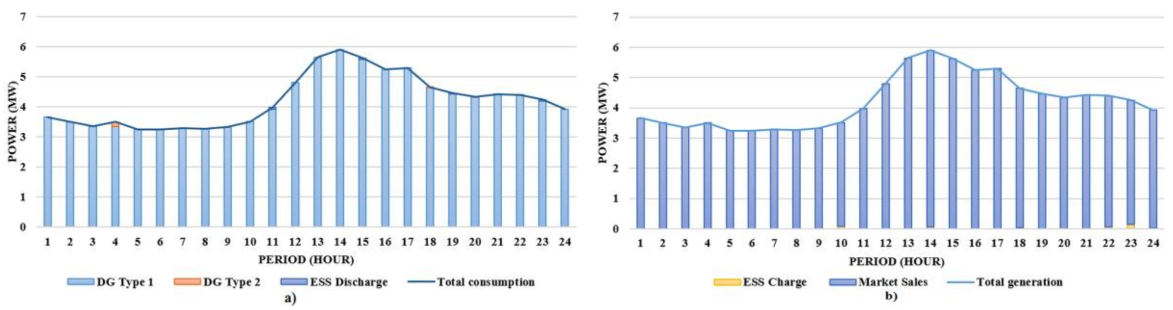


Figure 32 Day-ahead scheduling results for aggregator 4 regarding power a) generation; b) consumption.

Figure 33 presents the scheduling results for the energy resources of the EV aggregator. A total of 16.72 MWh was generated/consumed by the technologies of this aggregator which was the least out of all aggregators as is reflected in the price that was the lowest obtained. 16.48 MWh of EV charging, 0.06 MWh of ESS charging, and 0.18 MWh of WS market sales are all accounted for the consumption.

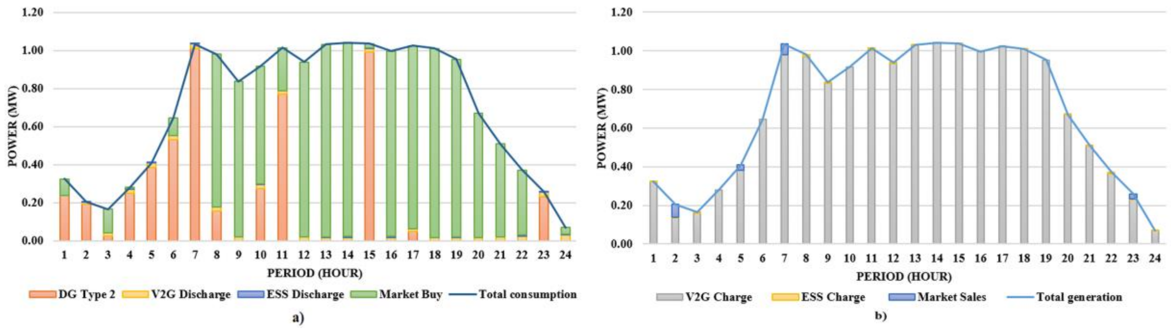


Figure 33 Day-ahead scheduling results for aggregator 5 regarding power a) generation; b) consumption.

The total generation is made up of 5.10 MWh of external supplier generation, 0.45 MWh of EV discharging, 0.05 MWh of ESS discharging, and 11.12 MWh of market bids. Even though the discharging costs considered were high the scheduled values were of small impact in the cost. The consumption was given by the charging of EVs in its majority with some ESS charging and some market sales from the excess of energy acquired from the external supplier, EV and ESS discharging, and some surplus of energy bought in the WS market.

The intraday costs of each aggregator for the proposed EAs are presented in Table 13 for one run. The costs in Table 13 are derived by adding the prices of the optimizations performed for each hour during a 24-hour period. The values in terms of costs should not vary greatly from day-ahead to intraday, because the intention is that the management in day-ahead is done well to then be checked in intraday when the uncertainty is less. In this case HC2RCEDUMDA presented the least variation for the first aggregator with no penalties added. For the second aggregator DE presented the least variation with a decrease of 0.57% in terms of total costs. HC2RCEDUMDA also presented the smallest variation from the day-ahead for the third and fourth aggregators.

When it comes to the third aggregator this algorithm presented a small penalty because for one period the demand was not equal to the supply in one of the evaluated scenarios. When it comes to the last aggregator all algorithms present a great variation from the day-ahead which is not ideal. DE and HC2RCEDUMDA display a greater disparity when compared to the other EAs with a significant amount of penalties added; that is, they were unable to develop a solution that satisfied the power balancing requirement.

Table 13 Intraday cost results, variation, penalties, and optimization time by the tested EAs.

EAs	Aggs	Avg. costs (m.u.)	Penalties (m.u.)	Variation (%)	Time (s)
DE	1	1,480.52	0.00	-1.88	2.01
	2	979.99	0.00	-0.57	1.95
	3	7,453.93	0.00	-4.36	2.45
	4	8,525.30	0.00	-1.34	2.20
	5	3,426.20	100.00	277.83	62.68
HyDE-DF	1	1,478.76	0.00	-1.99	2.00
	2	946.81	0.00	-3.94	2.06
	3	7,371.56	0.00	-5.42	2.09
	4	8,529.63	0.00	-1.29	2.02
	5	727.21	0.00	-19.80	69.56
DEEDA	1	1,472.92	0.00	-2.38	2.06
	2	934.22	0.00	-5.22	2.20
	3	7,317.26	0.67	-6.12	2.24
	4	8,525.34	0.00	-1.34	2.33
	5	713.26	0.00	-21.34	46.26
CUMDANCauchy++	1	1,472.92	0.00	-2.38	2.07
	2	934.22	0.00	-5.22	2.20
	3	7,317.53	0.67	-6.11	2.14
	4	8,525.41	0.00	-1.34	2.30
	5	713.26	0.00	-21.34	40.01
HC2RCEDUMDA	1	1,509.06	0.00	0.01	24.28
	2	1,050.01	0.00	6.53	23.50
	3	8,026.64	0.67	2.99	24.37
	4	8,532.23	0.00	-1.26	22.64
	5	4,267.04	200.00	370.56	88.92

The total costs of all aggregators obtained by each metaheuristic for the hour-ahead problem are presented in Figure 34. A consistent value of 19,836.63 m.u. is also shown for the total price of the day ahead optimization for comparison between all intraday optimizations. The algorithm that brought the slightest variation compared with the day-ahead was the HyDE-DF algorithm with a total value of 19,053.97 m.u., a slight decrease of 782.66 m.u. (3.95%). The DEEDA algorithm and the CUMDANCauchy++ algorithm presented similar total costs, with DEEDA obtaining a total cost of 18,962.99 m.u. and CUMDANCauchy getting a price of 18,963.34 m.u.. In this case, DEEDA showed the lowest prices in the entire system, presenting the best value in terms of operational costs with a 4.40% reduction. HC2RCEDUMDA and DE presented the worst overall costs, with the first having an increase of 17.89% concerning the day ahead and the second giving a total value of

21,865.94 m.u. (10.23%). DE and HC2RCEDUMDA gave these costs mainly due to the last aggregator, where the costs increased exponentially because of the added penalties.

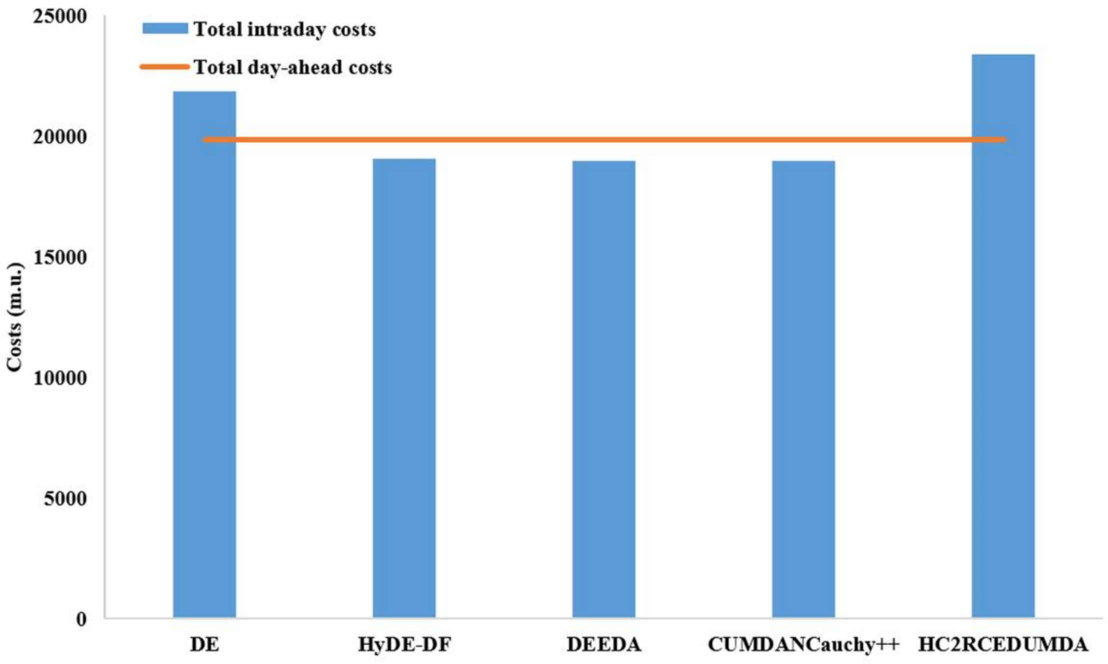


Figure 34 A comparison of the day-ahead total costs with the overall intraday costs generated by each EA.

The graphics containing the intraday scheduling of the energy resources of the proposed aggregators are presented considering the optimization of the EA which obtained the least variation costs from the day-ahead to the intraday, as shown in Table 13. Considering this situation, the HC2RCEDUMDA scheduling result for the first aggregator is presented in Figure 35. The total generation and consumption were 31.10 MWh which corresponded to 1.37 MWh from the day-ahead. On the consumption side, the values from the market sales are equal to the day-ahead, the total load increased from 29.31 MWh to 30.16 MWh, ESS charging corresponded to 0.03 MWh, and LEM sales were a total of 0.80 MWh. When it comes to the generation, the external supplier generation and market buys are equal to the day-ahead, 0.84 MWh of load reduction was obtained, 0.03 MWh of ESS discharging, and 2.51 MWh of LEM buys. The load increase and the LEM being superior from the sales result in increased costs, as presented in Table 13. In this situation, the LEM is used to purchase/sell energy by the aggregator to satisfy the existing load variations. The time horizon is closer to the real one, and the WS market and external supplier values are fixed at day-ahead. For the most part, the aggregator chooses to go to the LEM, with only a few values of charge/discharge of ESSs.

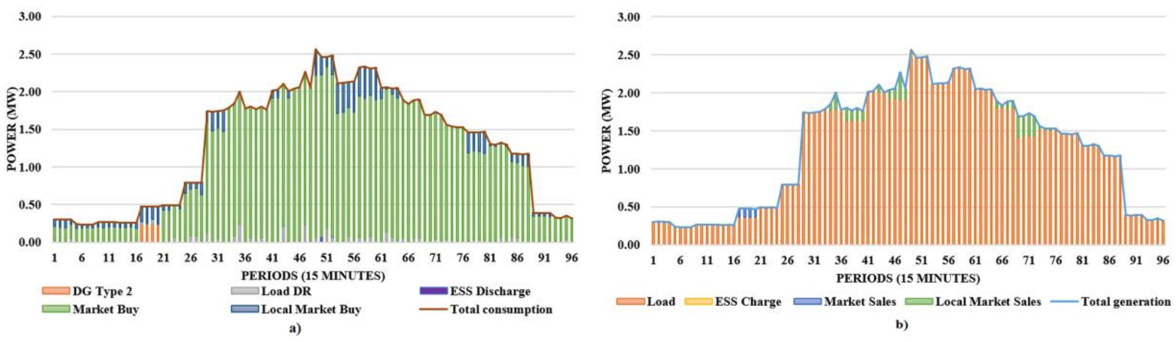


Figure 35 Hour-ahead scheduling results for aggregator 1 regarding power a) generation; b) consumption.

Figure 36 represents the hour-ahead results for the second aggregator for the DE optimization. The total energy obtained from generation/consumption in this model corresponded to 21.38 MWh, a slight increase from the day-ahead. In this situation, 19.94 MWh of residential load consumption resulted from the optimization, ESS charging values were almost null, and 0.39 MWh resulted from LEM sales. 1.14 MWh of load reduction and 0.29 MWh of LEM buys were obtained in the hour-ahead model. A slight reduction in costs results from this optimization due to the quantity of LEM sales being higher than LEM buys, and due to the considered prices, a small profit is obtained concerning the day-ahead.

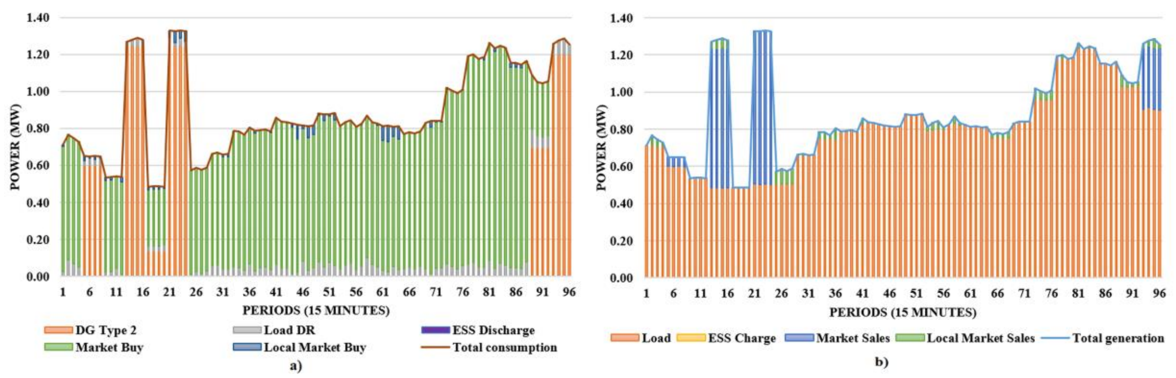


Figure 36 Hour-ahead scheduling results for aggregator 2 regarding power a) generation; b) consumption.

The intraday scheduling results of the third aggregator is represented in Figure 37.

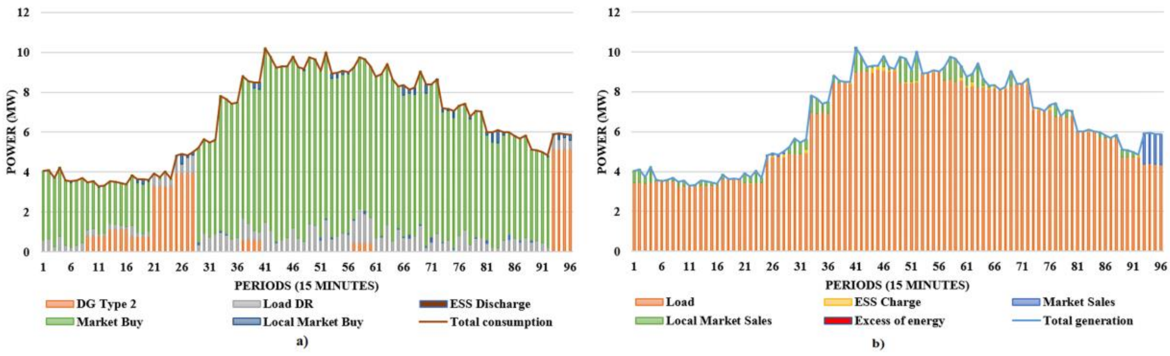


Figure 37 Hour-ahead scheduling results for aggregator 3 regarding power a) generation; b) consumption.

Due to the existence of a penalty in this aggregators optimization the generation is different from the consumption. In this case the generation corresponded to the 158.54 MWh and the consumption to 158.53 MWh with 5.9 kW of excess power in period 41. An increase of 10.09 MWh from the day-ahead was verified. Office loads account for 149.22 MWh of consumption, 0.86 MWh of ESS charging, WS market sales are equal to the day-ahead, and 6.85 MWh of LEM sales. External supplier generation, and WS market buys remain fixed from the day-ahead, 15.86 MWh of DR, 0.70 MWh of ESS discharging, and 1.82 MWh of LEM buys make up the entire generation. Due to the increase of consumption/generation, and the existence of penalties the increase in costs from the day-ahead is expected.

For the fourth aggregator the scheduling results of HC2RCEDUMDA are given in Figure 38. In this scenario, the total energy acquired from generation/consumption was 101.77 MWh. Since market solutions, and external supplier values are fixed from the day-ahead the LEM only needed to match renewable production variations that occurred, and ESS charging and discharging differences. In this case 99.78 MWh of generation from renewables was verified representing a small reduction from the day-ahead which corresponds to the decrease in costs verified since the generation costs considered are high. Values of 0.05 MWh of ESS discharging, and 1.78 MWh of LEM buys were also obtained in the generation side. In the consumption side the majority is given by the day ahead market solution with 0.09 MWh of ESS charging, and 1.29 MWh of LEM sales.

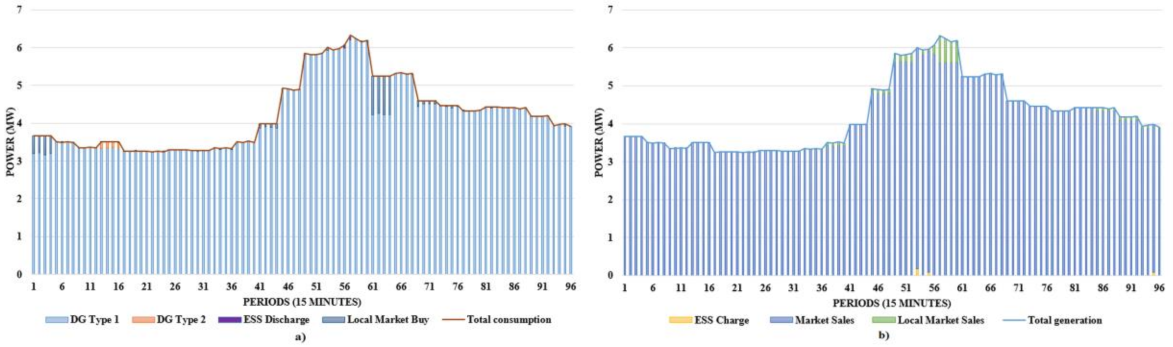


Figure 38 Hour-ahead scheduling results for aggregator 4 regarding power a) generation; b) consumption.

Figure 39 shows the outcomes of the fifth aggregator's intraday scheduling for the HyDE-DF optimization. The total energy obtained from generation/consumption in this situation was 18.06 MWh. Even though an increase in energy occurred in the hour-ahead model compared with the day-ahead the value obtained from LEM sales (4.21 MWh) was significantly higher than LEM buys (1.72 MWh) due to the reduction in EV charging that was verified (13.67 MWh) that the LEM had to compensate mainly in the first period of each hour of optimization. Because the LEM prices are higher than the WS market prices the decrease in costs is noticeable even though an increase in consumption/generation occurred.

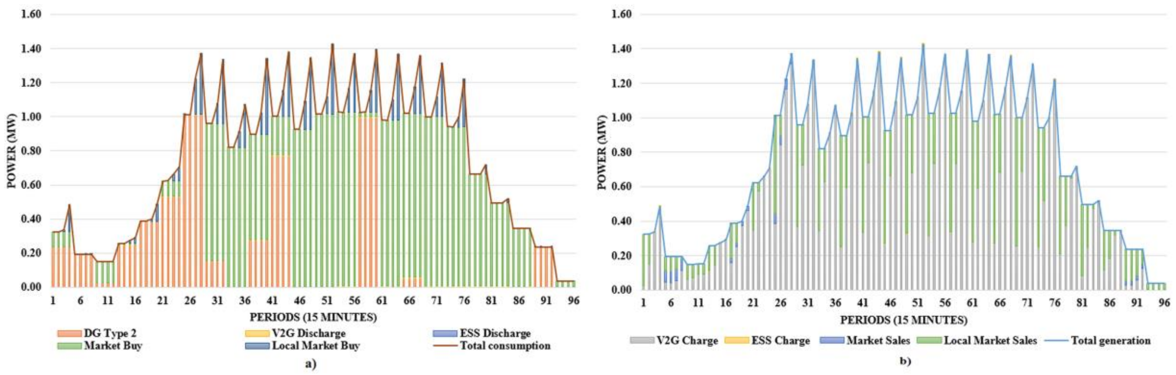


Figure 39 Hour-ahead scheduling results for aggregator 5 regarding power a) generation; b) consumption.

5.2. ALGORITHM PERFORMANCE

The performance of the EAs was tested for a total of 20 runs for hour-ahead model optimization. The overall results when for the 20 runs it comes to the intraday problem are presented in Table 14. The table provides the minimum and maximum cost values, the average and standard deviation in monetary units and percentages, due to the scale of the numbers acquired in the various aggregators for the objective function. When it comes to the optimization time for the first four aggregators the metaheuristics present similar values but for the last aggregator which is the aggregator with the most variables CUMDANCauchy is the fastest. From the standard deviation results DEEDA and CUMDAN present great percentages with values varying slightly between runs.

Table 14 Overall intraday results and optimization time by the tested EAs over 20 runs.

EAs	Aggs	Avg. Costs (m.u.)	Std. Costs (m.u.)	Min. Costs (m.u.)	Max. Costs (m.u.)	Avg. Penalties (m.u.)	Avg. Time (s)
DE	1	1,481.98	4.98 (0.34%)	1,476.32	1,495.86	0.00	2.05
	2	978.19	9.25 (0.95%)	963.07	997.97	0.00	2.46
	3	7,473.07	51.52 (0.69%)	7,387.53	7,591.33	0.00	1.98
	4	8,525.54	0.94 (0.01%)	8,525.30	8,529.41	0.00	2.16
	5	3,478.17	49.20 (1.41%)	3,386.13	3,576.12	100.00	61.44
HyDE-DF	1	1,479.70	3.33 (0.23%)	1,474.88	1,487.31	0.00	2.05
	2	945.11	4.08 (0.43%)	938.80	953.85	0.00	2.03
	3	7,371.48	23.60 (0.32%)	7,336.56	7,423.03	0.17	2.03
	4	8,527.98	4.13 (0.05%)	8,526.27	8,542.75	0.00	2.20
	5	727.42	4.74 (0.65%)	720.35	737.78	0.00	64.73
DEEDA	1	1,472.92	0.00 (0.00%)	1,472.92	1,472.93	0.00	1.97
	2	934.22	0.00 (0.00%)	934.22	934.23	0.00	2.20
	3	7,317.24	0.18 (0.00%)	7,316.98	7,317.59	0.67	2.20
	4	8,525.32	0.09 (0.00%)	8,525.30	8,525.70	0.00	2.36
	5	713.26	0.00 (0.00%)	713.26	713.26	0.00	46.01
CUMDANCauchy++	1	1,472.92	0.01 (0.00%)	1,472.92	1,472.95	0.00	2.27
	2	934.22	0.00 (0.00%)	934.22	934.22	0.00	2.07
	3	7,317.35	0.27 (0.00%)	7,317.13	7,318.29	0.67	2.12

	4	8,525.31	0.06 (0.00%)	8,525.30	8,525.57	0.00	2.17
	5	713.26	0.00 (0.00%)	713.26	713.27	0.00	41.69
HC2RCED UMDA	1	1,516.88	25.30 (1.67%)	1,479.81	1,575.26	0.00	24.07
	2	1,052.76	18.49 (1.76%)	1,019.28	1,088.99	0.00	22.89
	3	7,984.65	157.49 (1.97%)	7,713.67	8,320.24	0.50	23.78
	4	8,532.67	14.32 (0.17%)	8,525.99	8,579.71	0.00	22.19
	5	4,349.15	66.70 (1.53%)	4,234.71	4,469.32	235.00	89.39

The intraday results were also subjected to a Wilcoxon test, with a sample of 20 runs lasting 24 hours each. The CUMDANCauchy++ algorithm, as shown in Table 15, was used as the base algorithm for comparison with the others. The Wilcoxon test was applied to each set of results of the five aggregators. The statistical test's signal ranking is shown in Table 13.

Table 15 Results from the Wilcoxon signed-rank test.

		DE	**HyDE-DF**	**DEEDA**	**HC2RCEDUMDA**
Agg 1	**CUMDAN**	'+'	'+'	'+'	'+'
Agg 2		'+'	'+'	'='	'+'
Agg 3		'+'	'+'	'='	'+'
Agg 4		'='	'+'	'='	'+'
Agg 5		'+'	'+'	'='	'+'

It can be concluded that CUMDANCauchy++ outperforms HC2RCEDUMDA, and HyDE-DF for all aggregators. DE is also outperformed by CUMDANCauchy in all aggregators except for the fourth aggregator where they obtain similar results. DEEDA is only outperformed in the first aggregator with the remaining both algorithms obtain similar performance.

Figure 40 shows a brief example of each algorithm's convergence for a population of 20 individuals. In the 24th hour of the optimization, the first aggregator is put to the test. When compared to the other algorithms, CUMDANCauchy++ provides the best conversion, but the solution in both CUMDAN and HC2RCEDUMDA can still be improved. This could imply that some of the settings used, such as the number of iterations and the objective function evaluation limit, were not ideal. DE, HyDE-DF, and DEEDA, on the other hand, appear to have stabilized their fitness. Around generation 50, this last algorithm exhibits a rise in fitness. This peak depicts the algorithm's transaction from the DE to the EDA.

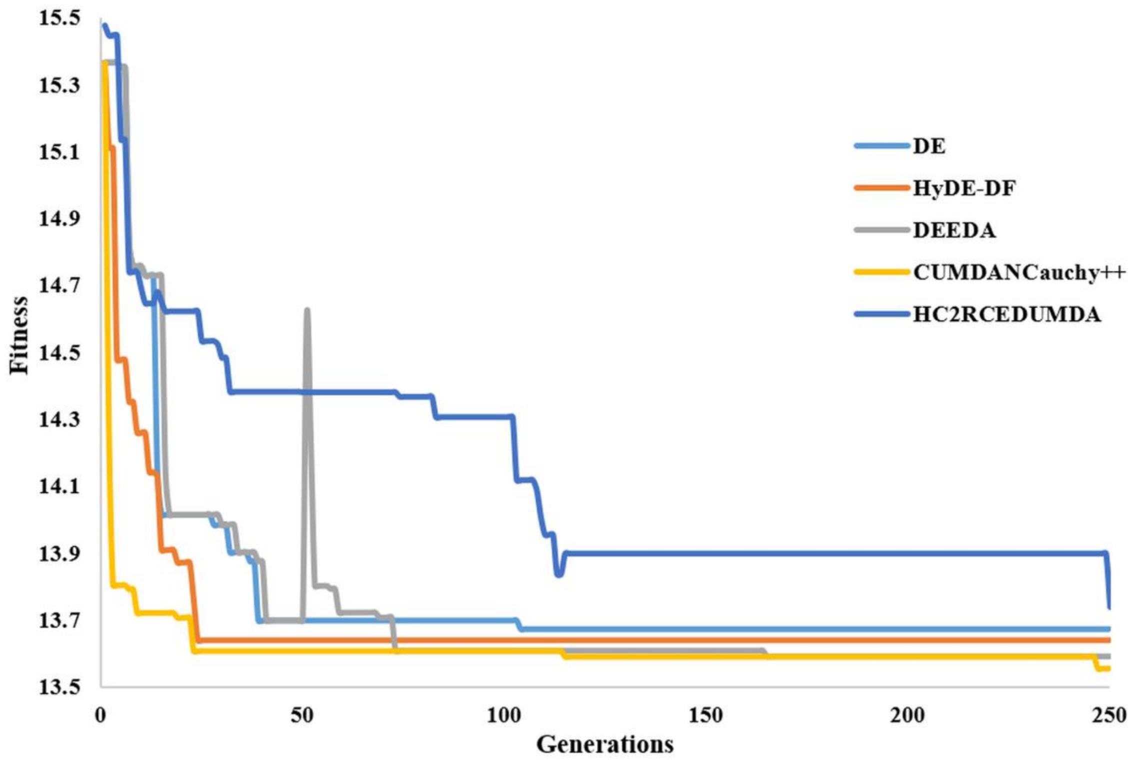


Figure 40 A comparison of the day-ahead overall costs with the overall intraday costs generated by each tested metaheuristic.

5.3. RISK-BASED STRATEGY RESULTS

The purpose of implementing a risk methodology is to minimize the costs associated with the risk of uncertainty for extreme scenarios. As such, two models were proposed, the first without risk aversion and the second considering 100% risk aversion. In the risk-neutral methodology, the aggregator scales to day-ahead based on expected cost, i.e., it considers the scenarios with the highest probability of occurrence. The aggregator already considers the worst-case scenario for the risk-averse strategy, as it adds to its objective function the risk measurement parameter.

The metaheuristic used to simulate the risk-based day-ahead scheduling was the CUMDANCauchy++, which from the previous section (Section 5.2) obtained the best overall performance when the Wilcoxon test was applied.

Table 16 shows the aggregators' multiple cost components for the risk-neutral and risk-averse strategies. It is possible to observe an increase of 787.66 m.u. in investment from the risk-neutral to the risk-averse approach, majorly given by the generation cost. The aggregator prevents itself by investing more in energy production in case some extreme event occurs. In this case, the costs from ENS are reduced around 70% from the risk-neutral to the risk-averse method, which is a significant improvement because the considered price for ENS in this methodology is 3,000 m.u./MWh which is considerably high. Since the aggregator has invested more in energy production when dispatching, the costs associated with the NES are reduced since it has more production at its disposal. When the risk measurement mechanism is considered, the cost associated with the penalties of violated variable limits is also slightly reduced (3 m.u.). Even though the expected cost increased by 1,322.65 m.u. from the risk-neutral strategy to the risk-averse strategy, the OF value was reduced by around 4,124.50 m.u., which corresponds to a 13.89% decrease. That is, the risk-based strategy implemented improved the results obtained in the cost of the extreme events, mainly in the worst scenario with a 51.83% reduction.

Table 16 Cost components in the proposed strategies.

Cost components	Risk-neutral (m.u.)	Risk-averse (m.u.)
Day-ahead investment (operational costs)	21,485.23	22,272.89
ENS costs	31.02	9.23
Generation costs	18,283.07	19,970.01
Market bid costs	3,171.15	2,293.66
Market offer revenue	1,494.86	956.88
Penalties	16.00	13.00
Total expected cost (Z_{ex})	20,006.37	21,329.02
$Z_{ex} + CVaR_{0.95}$	29,701.23	25,576.73
Worst scenario	84,232.70	40,571.52

Regarding the scheduling results obtained for the risk-based methodology, Figure 41 shows the day ahead scheduling results for the risk-neutral method. In this situation, the total generated energy obtained was 241.58 MWh, and the total energy consumed was 241.59 MWh, which corresponds to a total of 0.01 MWh of ENS. A total of 100.52 MWh of renewable generation, 73.42 MWh of external supplier generation, and 67.63 MWh of market bids correspond to the generation side. The consumption is given by 196.93 MWh of load demand, 13.08 MWh of EV charging, and 31.57 MWh of market offers. Due to the extreme scenarios considered, the ENS occurs in three of the 24 periods of optimization, which is not ideal for the aggregator. In this case, the extreme scenarios were the load increases, market capacity, and DR capacity decrease with the aggregator not having a mechanism to buy the energy needed to satisfy the load.

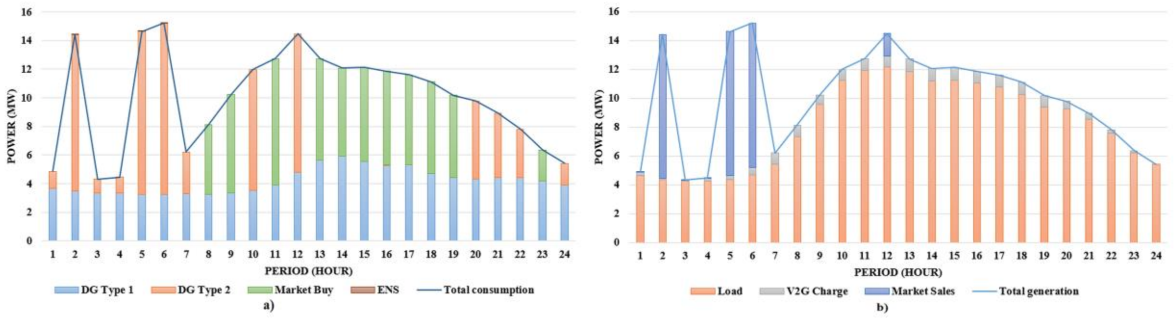


Figure 41 Day-ahead scheduling results for the risk-neutral strategy regarding power a) generation; b) consumption.

Figure 42 presents the day ahead scheduling results for the risk-averse strategy. The total energy/consumed was 229.58 MWh with only 3.08 kWh of ENS, a reduction of 70% from the previous case. This situation of ENS was only verified in period one, where previously the ENS was verified in periods 2,5, and 6. When it comes to the generation, a total of 100.52 MWh of renewables was again obtained. A total of 79.11 MWh of external supplier generation was acquired, an increase from the risk-neutral strategy, reflecting the rise in generation costs shown in Table 15. A total of 49.94 MWh of market bid energy was also verified on the generation side. The load demand and EV charging energy values remained equal to the risk-neutral method, with the market offer varying from 31.57 MWh to 19.57 MWh.

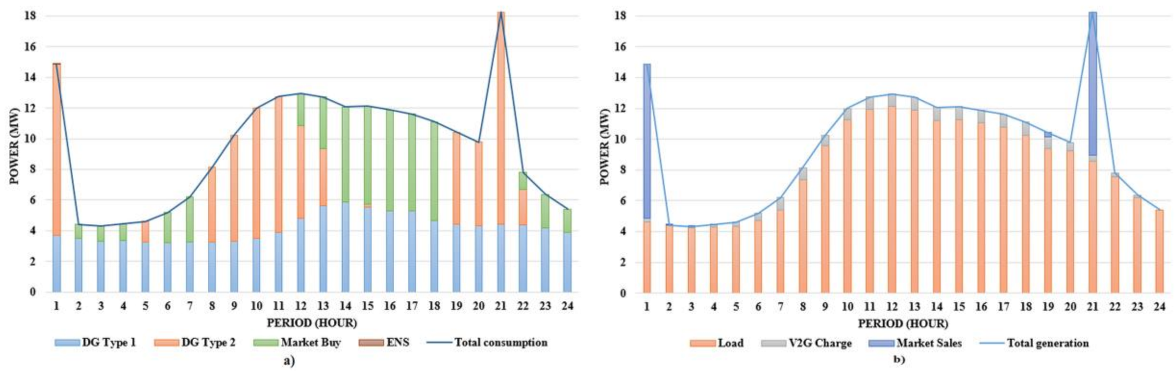


Figure 42 Day-ahead scheduling results for the risk-averse strategy regarding power a) generation; b) consumption.

From these values, it can be concluded that the risk-averse strategy mainly acted when it comes to market offer/bids to reduce penalties and ENS since, in some extreme scenarios, market capacity is highly reduced. In both cases, but especially in the risk-neutral, the aggregator, due to the significant increase in market prices in some of the scenarios, prefers to buy energy from the external supplier to sell in the market to make a profit, not being interested in the penalty assigned to the ENS, not even using the ESSs, and EVs to meet the power balance constraint.

The total cost of each scenario for both risk strategies is shown in Figure 43, representing the number of the specific extreme scenarios. From the figure, it is possible to observe that the extreme scenarios considered have mostly higher costs. In terms of the worst scenario, a significant reduction can be noticed from the risk-neutral to the risk-averse. This scenario is scenario 22, the third extreme scenario generated, given by the decrease in the external supplier maximum limit.

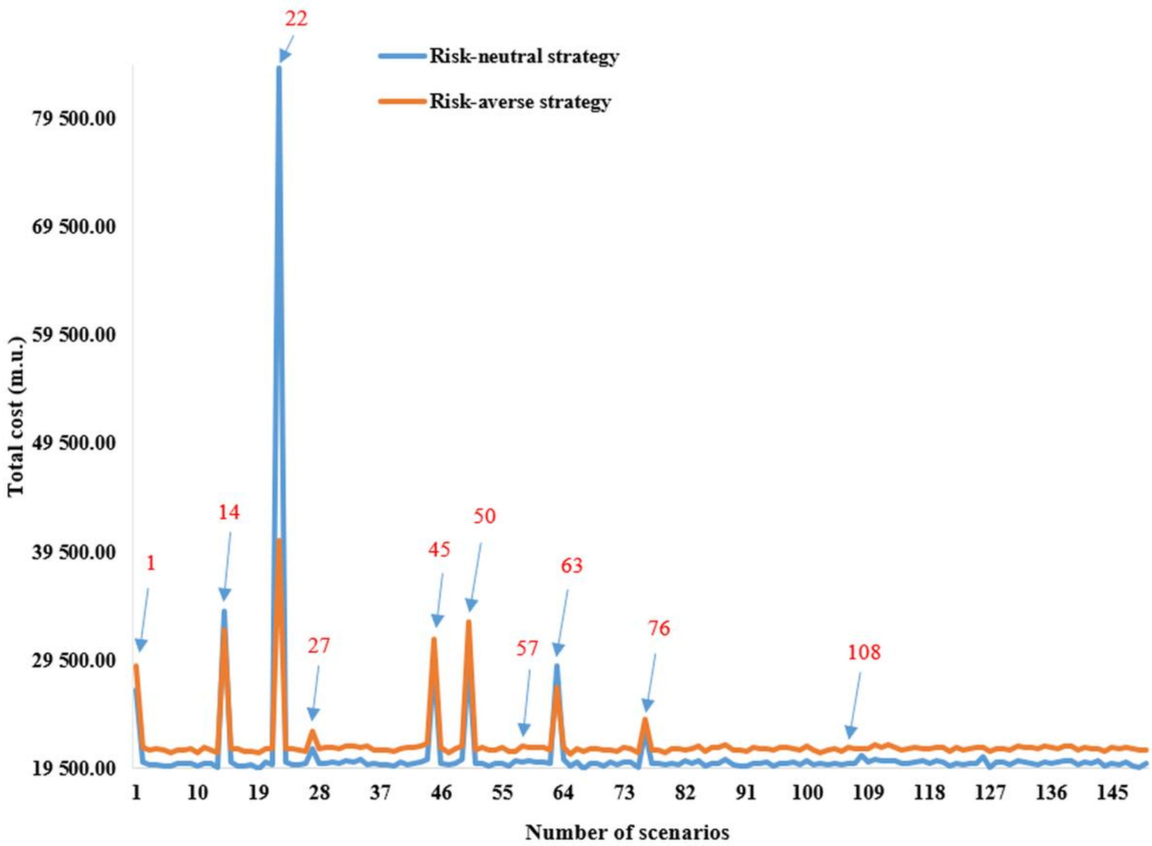


Figure 43 Total scenario cost for risk-neutral and risk-averse approaches.

It is also worth noticing that in some extreme scenarios generated, such as scenarios 57, and 108 the increase in costs was minimal compared to the remaining. These two scenarios correspond to the seventh, and tenth extreme scenarios created in which both include an increase in market prices and the first includes an external supplier capacity reduction and the second a DR limit reduction (Section 4.3). Also, in this situation, the metaheuristic majorly focused on reducing the cost of the worst scenario with the cost of some extreme scenarios even increasing, as seen in the figure.

5.4. CHAPTER CONCLUSIONS

The results for resource scheduling considering multiple aggregators for the hour-ahead time horizon have been presented in this chapter. Initially, a comparison is made with day-ahead in terms of cost variation for the EAs used. The smallest variation was chosen for the presentation of the scheduling graphs. It was found that HC2RCEDUMDA presented good values in the intraday simulation for aggregators 1, 3, and 4 even though it presented penalties for not meeting the energy balance constraint in the third one. The DE and HyDE-DF also showed promising results in terms of cost variation from day-ahead to intraday. The DE with the smallest increase for the second aggregator and the HyDE-DF with the best value presented in intraday for the EVs aggregator. This one has a high number of variables and constraints, which makes the problem more complex for this aggregator. In terms of performance, through a mean and standard deviation test and a statistical test, it was possible to see that CUMDANCauchy++ presented the best performance. Also, in this chapter, the results for the simulations that consider the risk scenarios were presented. The risk aversion methodology seems more advantageous for the aggregator because it reduces the costs of the OF from risk-averse to risk-neutral even though the operational costs are more expensive, i.e., even making a more significant investment.

6. CONCLUSIONS

This chapter provides the conclusions to the developed work when considering the intraday ERM for multiple aggregators, and the risk-based optimal ERM in the day-ahead. The projected work for the future taking into consideration the model described is also presented.

6.1. FINAL CONCLUSIONS

Given the significant penetration of distributed energy resources in a DN, this thesis provided several aggregators' efficient intraday energy resource scheduling. The intraday management used an hour-ahead model with four 15-minute periods and transactions on a LEM to meet the energy balance equation. To plan their available resources, the optimization problem was solved using several metaheuristics.

In the optimization model each of the five aggregators must consider the day-ahead management results, the results of the previous hour of optimization, and the intraday uncertainty. A low variation should be expected when comparing hour-ahead to day-ahead results, so that the day-ahead scheduling has been well made. Still, a slight increase in costs is expected in relation to the day-ahead due to the variation in forecasts (more accurate forecasts). In some cases, because of the stochastic nature of the metaheuristics', some aggregators decrease their intraday costs. In fact, it was verified that the first four aggregators presented variations up to the 5% mark with the best results having less than a 3% increase/decrease. It can be stated that the adopted method is particularly weak when it comes to the EV aggregator (aggregator 5) because there are significant differences when compared to the day-ahead around a 20% decrease in costs is verified in three EAs with DE and HC2RCEDUMDA presenting the highest increase in excess of 300%. In this situation, a signaling method [22] could be implemented for EV charging. Due to the minimal number of variables in the hour-ahead model and low optimization time obtained, a deterministic approach could also be preferable since it allows an optimal solution.

CUMDANCauchy++, the winner of the "2020 Competition on Evolutionary Computation in the Energy Domain: Smart Grid Applications" that addressed an energy resource scheduling optimization problem was compared to the other optimization algorithms, namely DE, HyDE-DF, DEEDA, and HC2RCEDUMDA, using a signed-rank statistical test. As expected, CUMDANCauchy++ was quite competitive in this problem, losing primarily on aggregator three versus DE, HyDE-DF, and DEEDA, and aggregator four against DE. This method and the DEEDA algorithm perform similarly on most simulations, recalling that DEEDA, similarly to CUMDANCauchy, uses an EDA to generate a new population using Normal and Cauchy distributions. It is possible to conclude that algorithms that incorporate EDAs present better performance for the ERM problem.

A risk-based methodology was also applied for the day-ahead scheduling problem when considering one aggregator in the DN. The results suggest claiming that the risk mechanism allows obtaining a better and more robust solution even with the 4% increase in operational costs and the 6.2% increase in expected costs. This situation occurs by reducing the risk measuring parameters (VaR and CVaR) and the cost of the worst-case scenario. In other words, by opting for this solution, the aggregator reduces its risk in the event that the worse scenarios happen, namely with a 13.86% reduction in cost.

6.2. FUTURE WORK

For future work, it is necessary to perform a scenario generation similar to what was done in the day-ahead to obtain more precise results. The proposed hour-ahead model should be improved because the optimization is done independently for each hour in this work, thus losing the possibility of shifting the load/discharge of ESSs and EVs to more favorable periods. A comparison of the solutions obtained through metaheuristics with deterministic methods will also be performed to determine which method is best to implement.

The network constraints were not initially considered for the proposed model, as the aggregators are limited to only performing the ERM independent of each other without DSO communication. It is required to perform an analysis of the congestion and constraints imposed on DN for the results obtained in the scheduling of each aggregator through power flow and optimal power flow techniques. Flexibility strategies to manage congestion and network violations will also be implemented for the outcomes obtained.

As far as the risk strategy is concerned, it will be implemented for the day-ahead and intraday, considering all the aggregators proposed here to evaluate the safety of their solutions when considering worst-case scenarios. To this end, a tool for creating these risk scenarios will be implemented, since for this work the extreme scenarios were created manually. A risk factor (β) analysis will also be implemented, perhaps considering various confidence levels of α.

References

[1] A. Ferreira dos Santos and J. Tomé Saraiva, "Agent Based Models in Power Systems: A Literature Review," *UPorto J. Eng.*, vol. 7, no. 3, pp. 101–113, Apr. 2021, doi: 10.24840/2183-6493_007.003_0009.

[2] J. Almeida, J. Soares, B. Canizes, I. Razo-Zapata, and Z. Vale, "Intraday Energy Resource Scheduling for Load Aggregators Considering Local Market," in *16th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2021)*, Cham, 2022, pp. 233–242. doi: 10.1007/978-3-030-87869-6_22.

[3] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local Energy Markets: Paving the Path Toward Fully Transactive Energy Systems," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4081–4088, 2019, doi: 10.1109/TPWRS.2018.2833959.

[4] Í. Munné-Collado, E. Bullich-Massagué, M. Aragüés-Peñalba, and P. Olivella-Rosell, "Local and Micro Power Markets," in *Micro and Local Power Markets*, John Wiley & Sons, Ltd, 2019, pp. 37–96. doi: 10.1002/9781119434573.ch2.

[5] J. Almeida, J. Soares, B. Canizes, and Z. Vale, "Coordination strategies in distribution network considering multiple aggregators and high penetration of electric vehicles," in *14th International Symposium Intelligent Systems 2020*, 2020, vol. 00, pp. 0–7.

[6] M. Ahmadi, M. Ono, M. D. Ingham, R. M. Murray, and A. D. Ames, "Risk-Averse Planning Under Uncertainty," in *2020 American Control Conference (ACC)*, Denver, CO, USA, Jul. 2020, pp. 3305–3312. doi: 10.23919/ACC45564.2020.9147792.

[7] S. Bruno, S. Ahmed, A. Shapiro, and A. Street, "Risk neutral and risk averse approaches to multistage renewable investment planning under uncertainty," *Eur. J. Oper. Res.*, vol. 250, no. 3, pp. 979–989, May 2016, doi: 10.1016/j.ejor.2015.10.013.

[8] O. Kramer, *Genetic Algorithm Essentials*, vol. 679. Cham: Springer International Publishing, 2017. doi: 10.1007/978-3-319-52156-5.

[9] M. Schoenauer, Ed., *Parallel problem solving from nature - PPSN VI: 6th International Conference, Paris, France, September 2000 ; proceedings*. Berlin ; New York: Springer, 2000.

[10] R. Storn and K. Price, "Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces," *J. Glob. Optim.*, vol. 11, pp. 341–359, 1997, doi: 10.1071/AP09004.

[11] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proceedings of ICNN’95 - International Conference on Neural Networks*, Perth, WA, Australia, 1995, vol. 4, pp. 1942–1948. doi: 10.1109/ICNN.1995.488968.

[12] Jun Sun, Wenbo Xu, and Bin Feng, “A global search strategy of quantum-behaved particle swarm optimization,” in *IEEE Conference on Cybernetics and Intelligent Systems, 2004.*, Singapore, 2005, vol. 1, pp. 111–116. doi: 10.1109/ICCIS.2004.1460396.

[13] S. Mostaghim and J. Teich, “Strategies for finding good local guides in multi-objective particle swarm optimization (MOPSO),” in *Proceedings of the 2003 IEEE Swarm Intelligence Symposium. SIS’03 (Cat. No.03EX706)*, Indianapolis, IN, USA, 2003, pp. 26–33. doi: 10.1109/SIS.2003.1202243.

[14] M. A. Shoorehdeli, M. Teshnehlab, and A. K. Sedigh, “Novel Hybrid Learning Algorithms for Tuning ANFIS Parameters Using Adaptive Weighted PSO,” in *2007 IEEE International Fuzzy Systems Conference*, London, UK, Jun. 2007, pp. 1–6. doi: 10.1109/FUZZY.2007.4295571.

[15] M. G. H. Omran and M. Mahdavi, “Global-best harmony search,” *Appl. Math. Comput.*, vol. 198, no. 2, pp. 643–656, May 2008, doi: 10.1016/j.amc.2007.09.004.

[16] P. Civicioglu, “Transforming geocentric cartesian coordinates to geodetic coordinates by using differential search algorithm,” *Comput. Geosci.*, vol. 46, pp. 229–247, Sep. 2012, doi: 10.1016/j.cageo.2011.12.011.

[17] J. Soares, M. A. Fotouhi Ghazvini, M. Silva, and Z. Vale, “Multi-dimensional signaling method for population-based metaheuristics: Solving the large-scale scheduling problem in smart grids,” *Swarm Evol. Comput.*, vol. 29, pp. 13–32, 2016, doi: 10.1016/j.swevo.2016.02.005.

[18] J. F. Franco, M. Lavorato, R. Romero, and N. Ba, “Metaheuristic optimization algorithms for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation,” vol. 142, pp. 351–361, 2017, doi: 10.1016/j.epsr.2016.09.018.

[19] J. Soares, F. Lezama, B. Canizes, and Z. Vale, “WCCI/GECCO 2020 Competition Evolutionary Computation in Uncertain Environments: A Smart Grid Application,” p. 21.

[20] J. Soares, H. Morais, T. Sousa, Z. Vale, and P. Faria, “Day-ahead resource scheduling including demand response for electric vehicles,” *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 596–605, 2013, doi: 10.1109/TSG.2012.2235865.

[21] F. Lezama, L. E. Sucar, E. M. De Cote, J. Soares, and Z. Vale, “Differential evolution strategies for large-scale energy resource management in smart grids,” *GECCO 2017 - Proc. Genet. Evol. Comput. Conf. Companion*, pp. 1279–1286, 2017, doi: 10.1145/3067695.3082478.

[22] J. Soares, N. Borges, Z. Vale, and P. B. De Moura Oliveira, “Enhanced multi-objective energy optimization by a signaling method,” *Energies*, vol. 9, no. 10, 2016, doi: 10.3390/en9100807.

[23] N. H. Awad, M. Z. Ali, R. Mallipeddi, and P. N. Suganthan, “An efficient Differential Evolution algorithm for stochastic OPF based active–reactive power dispatch problem considering renewable generators,” *Appl. Soft Comput. J.*, vol. 76, pp. 445–458, 2019, doi: 10.1016/j.asoc.2018.12.025.

[24] F. Lezama, J. Soares, R. Faia, and Z. Vale, “Hybrid-adaptive differential evolution with decay function (Hyde-DF) applied to the 100-digit challenge competition on single objective numerical optimization,” *GECCO 2019 Companion - Proc. 2019 Genet. Evol. Comput. Conf. Companion*, pp. 7–8, 2019, doi: 10.1145/3319619.3326747.

[25] F. Lezama, J. Soares, R. Faia, T. Pinto, and Z. Vale, “A New Hybrid-Adaptive Differential Evolution for a Smart Grid Application under Uncertainty,” *2018 IEEE Congr. Evol. Comput. CEC 2018 - Proc.*, 2018, doi: 10.1109/CEC.2018.8477808.

[26] J. Soares, F. Lezama, Z. Vale, S. Brisset, and B. Francois, “Safety Isolating Transformer Design using HyDE-DF algorithm,” *2020 IEEE Congr. Evol. Comput. CEC 2020 - Conf. Proc.*, vol. 2017, 2020, doi: 10.1109/CEC48606.2020.9185619.

[27] F. Lezama, J. Soares, and Z. Vale, “Optimal Bidding in Local Energy Markets using Evolutionary Computation,” *2019 20th Int. Conf. Intell. Syst. Appl. Power Syst. ISAP 2019*, pp. 4–9, 2019, doi: 10.1109/ISAP48318.2019.9065976.

[28] Y. Martínez-López, J. Madera, A. Moya, M. Bethencourt, and A. Y. R. González, “DEEDA Differential Evolutionary and Estimation of Distribution Algorithm,” p. 2.

[29] Y. Martínez-López, A. Y. Rodríguez-González, J. M. Quintana, A. Moya, B. Morgado, and M. B. Mayedo, “CUMDANCauchy-C1: a cellular EDA designed to solve the energy resource management problem under uncertainty,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, Prague Czech Republic, Jul. 2019, pp. 13–14. doi: 10.1145/3319619.3326743.

[30] Y. Martínez-López, A. Y. Rodríguez-González, J. M. Quintana, M. B. Mayedo, A. Moya, and O. M. Santiago, “Applying some EDAs and hybrid variants to the ERM problem under uncertainty,” in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion*, Cancún Mexico, Jul. 2020, pp. 1–2. doi: 10.1145/3377929.3398393.

[31] F. Lezama, J. Soares, B. Canizes, Z. Vale, and R. Romero, “Guidelines for PES-GM/CEC/GECCO 2021 Competition Evolutionary Computation in the Energy Domain: Smart Grid Applications,” p. 17.

[32] A. Y. Rodríguez-González, S. Barajas, R. Aranda, Y. Martínez-López, and J. Madera-Quintana, “Ring cellular encode-decode UMDA: simple is effective,” in *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, Lille France, Jul. 2021, pp. 1–2. doi: 10.1145/3449726.3463278.

[33] N. S. Nafi, K. Ahmed, M. A. Gregory, and M. Datta, “A survey of smart grid architectures, applications, benefits and standardization,” *J. Netw. Comput. Appl.*, vol. 76, pp. 23–36, Dec. 2016, doi: 10.1016/j.jnca.2016.10.003.

[34] International Energy Agency, *Electricity Market Report, July 2021*. OECD, 2021. doi: 10.1787/f4044a30-en.

[35] B. Vedik, R. Kumar, R. Deshmukh, S. Verma, and C. K. Shiva, “Renewable Energy-Based Load Frequency Stabilization of Interconnected Power Systems Using Quasi-Oppositional Dragonfly Algorithm,” *J. Control Autom. Electr. Syst.*, vol. 32, no. 1, pp. 227–243, Feb. 2021, doi: 10.1007/s40313-020-00643-3.

[36] G. Dileep, “A survey on smart grid technologies and applications,” *Renew. Energy*, vol. 146, pp. 2589–2625, 2020, doi: 10.1016/j.renene.2019.08.092.

[37] K. K. Zame, C. A. Brehm, A. T. Nitica, C. L. Richard, and G. D. Schweitzer, “Smart grid and energy storage: Policy recommendations,” *Renew. Sustain. Energy Rev.*, vol. 82, no. July 2016, pp. 1646–1654, 2018, doi: 10.1016/j.rser.2017.07.011.

[38] M. E. El-Hawary, “The smart grid - State-of-the-art and future trends,” *Electr. Power Compon. Syst.*, vol. 42, no. 3–4, pp. 239–250, 2014, doi: 10.1080/15325008.2013.868558.

[39] “The Paris Agreement | UNFCCC.” https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement (accessed Feb. 07, 2021).

[40] “Employment multipliers for investment in the transport sector – Charts – Data & Statistics - IEA.” https://www.iea.org/data-and-statistics/charts/employment-multipliers-for-investment-in-the-transport-sector (accessed Feb. 11, 2021).

[41] “Sector by sector: where do global greenhouse gas emissions come from? - Our World in Data.” https://ourworldindata.org/ghg-emissions-by-sector (accessed Feb. 07, 2021).

[42] “Global EV Outlook 2021,” p. 101, 2021.

[43] N. Banol Arias, S. Hashemi, P. B. Andersen, C. Traeholt, and R. Romero, “Distribution System Services Provided by Electric Vehicles: Recent Status, Challenges, and Future Prospects,” *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 12, pp. 4277–4296, 2019, doi: 10.1109/TITS.2018.2889439.

[44] J. Wang *et al.*, “Performance evaluation of distributed energy resource management via advanced hardware-in-the-loop simulation,” *2020 IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. ISGT 2020*, pp. 2–6, 2020, doi: 10.1109/ISGT45199.2020.9087667.

[45] “DID U KNOW? | Quick Info about Power Systems Markets.” http://www.fi-powerweb.com/Did-You-Know.html (accessed Feb. 07, 2021).

[46] S. Prakesh, S. Sherine, and B. BIST, “Forecasting methodologies of solar resource and PV power for smart grid energy management,” *Int. J. Pure Appl. Math.*, vol. 116, no. 18, pp. 313–318, 2017.

[47] Q. Shi *et al.*, “Network reconfiguration and distributed energy resource scheduling for improved distribution system resilience,” *Int. J. Electr. Power Energy Syst.*, vol. 124, no. March 2020, p. 106355, 2021, doi: 10.1016/j.ijepes.2020.106355.

[48] J. Garcia-Guarin, D. Alvarez, A. Bretas, and S. Rivera, “Schedule optimization in a smart microgrid considering demand response constraints,” *Energies*, vol. 13, no. 17, 2020, doi: 10.3390/en13174567.

[49] S. G. M. Rokni, M. Radmehr, and A. Zakariazadeh, “Optimum energy resource scheduling in a microgrid using a distributed algorithm framework,” *Sustain. Cities Soc.*, vol. 37, no. November 2017, pp. 222–231, 2018, doi: 10.1016/j.scs.2017.11.016.

[50] V. S. Tabar, M. A. Jirdehi, and R. Hemmati, “Energy management in microgrid based on the multi objective stochastic programming incorporating portable renewable energy resource as demand response option,” *Energy*, vol. 118, pp. 827–839, 2017, doi: 10.1016/j.energy.2016.10.113.

[51] S. E. Ahmadi and N. Rezaei, “A new isolated renewable based multi microgrid optimal energy management system considering uncertainty and demand response,” *Int. J. Electr. Power Energy Syst.*, vol. 118, no. September 2019, p. 105760, 2020, doi: 10.1016/j.ijepes.2019.105760.

[52] R. Deng, Z. Yang, M. Y. Chow, and J. Chen, “A survey on demand response in smart grids: Mathematical models and approaches,” *IEEE Trans. Ind. Inform.*, vol. 11, no. 3, pp. 570–582, 2015, doi: 10.1109/TII.2015.2414719.

[53] J. Vardakas, N. Zorba, and C. Verikoukis, “A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms,” *IEEE Commun. Surv. Tutor.*, vol. 17, no. 1, pp. 152–178, 2015, doi: 10.1109/COMST.2014.2341586.

[54] F. Lezama, J. Soares, R. Faia, Z. Vale, L. H. Macedo, and R. Romero, “Business models for flexibility of electric vehicles: Evolutionary computation for a successful implementation,” *GECCO 2019 Companion - Proc. 2019 Genet. Evol. Comput. Conf. Companion*, pp. 1873–1878, 2019, doi: 10.1145/3319619.3326807.

[55] I. Pavic, T. Capuder, and I. Kuzle, “A comprehensive approach for maximizing flexibility benefits of electric vehicles,” *IEEE Syst. J.*, vol. 12, no. 3, pp. 2882–2893, 2018, doi: 10.1109/JSYST.2017.2730234.

[56] “Access to Electric Vehicles data for smart charging - Florence School of Regulation.” https://fsr.eui.eu/access-to-electric-vehicles-data-for-smart-charging/ (accessed Feb. 07, 2021).

[57] O. Frendo, N. Gaertner, and H. Stuckenschmidt, “Real-Time Smart Charging Based on Precomputed Schedules,” *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6921–6932, Nov. 2019, doi: 10.1109/TSG.2019.2914274.

[58] N. Daina, A. Sivakumar, and J. W. Polak, “Electric vehicle charging choices: Modelling and implications for smart charging services,” *Transp. Res. Part C Emerg. Technol.*, vol. 81, pp. 36–56, Aug. 2017, doi: 10.1016/j.trc.2017.05.006.

[59] A. Soroudi and A. Keane, *Plug In Electric Vehicles in Smart Grids*, vol. 89. 2015.

[60] M. Kumar, S. Vyas, and A. Datta, "A Review on Integration of Electric Vehicles into a Smart Power Grid and Vehicle-to-Grid Impacts," *2019 8th Int. Conf. Power Syst. Transit. Sustain. Smart Flex. Grids ICPS 2019*, 2019, doi: 10.1109/ICPS48983.2019.9067330.

[61] D. Wang, J. Coignard, T. Zeng, C. Zhang, and S. Saxena, "Quantifying electric vehicle battery degradation from driving vs. vehicle-to-grid services," *J. Power Sources*, vol. 332, pp. 193–203, Nov. 2016, doi: 10.1016/j.jpowsour.2016.09.116.

[62] J. Kester, L. Noel, G. Zarazua de Rubens, and B. K. Sovacool, "Promoting Vehicle to Grid (V2G) in the Nordic region: Expert advice on policy mechanisms for accelerated diffusion," *Energy Policy*, vol. 116, pp. 422–432, May 2018, doi: 10.1016/j.enpol.2018.02.024.

[63] J. Kester, G. Zarazua de Rubens, B. K. Sovacool, and L. Noel, "Public perceptions of electric vehicles and vehicle-to-grid (V2G): Insights from a Nordic focus group study," *Transp. Res. Part Transp. Environ.*, vol. 74, pp. 277–293, Sep. 2019, doi: 10.1016/j.trd.2019.08.006.

[64] A. Gubina, IEEE Power & Energy Society, Univerza v Ljubljani. Fakulteta za elektrotehniko, and Institute of Electrical and Electronics Engineers, "A Local Electricity Trading Market: Security Analysis," 2016.

[65] F. Teotia and R. Bhakar, "Local energy markets: Concept, design and operation," in *2016 National Power Systems Conference (NPSC)*, Bhubaneswar, India, Dec. 2016, pp. 1–6. doi: 10.1109/NPSC.2016.7858975.

[66] M. Ampatzis, P. H. Nguyen, and W. Kling, "Local electricity market design for the coordination of distributed energy resources at district level," in *IEEE PES Innovative Smart Grid Technologies, Europe*, Istanbul, Turkey, Oct. 2014, pp. 1–6. doi: 10.1109/ISGTEurope.2014.7028888.

[67] E. Mengelkamp, P. Staudt, J. Garttner, C. Weinhardt, and J. Huber, "Quantifying Factors for Participation in Local Electricity Markets," in *2018 15th International Conference on the European Energy Market (EEM)*, Lodz, Jun. 2018, pp. 1–5. doi: 10.1109/EEM.2018.8469969.

[68] Y. Tohidi, M. Farrokhseresht, and M. Gibescu, "A review on coordination schemes between local and central electricity markets," *Int. Conf. Eur. Energy Mark. EEM*, vol. 2018-June, pp. 1–5, 2018, doi: 10.1109/EEM.2018.8470004.

[69] A. Lüth, J. Weibezahn, and J. M. Zepter, "On Distributional Effects in Local Electricity Market Designs—Evidence from a German Case Study," *Energies*, vol. 13, no. 8, p. 1993, Apr. 2020, doi: 10.3390/en13081993.

[70] M. Lovati, X. Zhang, P. Huang, C. Olsmats, and L. Maturi, "Optimal Simulation of Three Peer to Peer (P2P) Business Models for Individual PV Prosumers in a Local

Electricity Market Using Agent-Based Modelling," *Buildings*, vol. 10, no. 8, p. 138, Jul. 2020, doi: 10.3390/buildings10080138.

[71] W. Mensi, S. J. H. Shahzad, S. Hammoudeh, R. Zeitun, and M. U. Rehman, "Diversification potential of Asian frontier, BRIC emerging and major developed stock markets: A wavelet-based value at risk approach," *Emerg. Mark. Rev.*, vol. 32, pp. 130–147, Sep. 2017, doi: 10.1016/j.ememar.2017.06.002.

[72] J. Chen, "On Exactitude in Financial Regulation: Value-at-Risk, Expected Shortfall, and Expectiles," *Risks*, vol. 6, no. 2, p. 61, Jun. 2018, doi: 10.3390/risks6020061.

[73] X. Cao, J. Wang, J. Wang, and B. Zeng, "A Risk-Averse Conic Model for Networked Microgrids Planning With Reconfiguration and Reorganizations," *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 696–709, Jan. 2020, doi: 10.1109/TSG.2019.2927833.

[74] M. Roustai, M. Rayati, A. Sheikhi, and A. Ranjbar, "A scenario-based optimization of Smart Energy Hub operation in a stochastic environment using conditional-value-at-risk," *Sustain. Cities Soc.*, vol. 39, pp. 309–316, May 2018, doi: 10.1016/j.scs.2018.01.045.

[75] A. Narayan and K. Ponnambalam, "Risk-averse stochastic programming approach for microgrid planning under uncertainty," *Renew. Energy*, vol. 101, pp. 399–408, Feb. 2017, doi: 10.1016/j.renene.2016.08.064.

[76] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-khah, and P. Siano, "Optimal bidding of profit-seeking virtual associations of smart prosumers considering peer to peer energy sharing strategy," *Int. J. Electr. Power Energy Syst.*, vol. 132, p. 107175, Nov. 2021, doi: 10.1016/j.ijepes.2021.107175.

[77] K. Alvehag, "Impact of dependencies in risk assessment of power distribution systems," Electric Power Systems, School of Electrical Engineering, Royal Institute of Technology, Stockholm, 2008.

[78] M. Esmaeeli, A. Kazemi, H. Shayanfar, G. Chicco, and P. Siano, "Risk-based planning of the distribution network structure considering uncertainties in demand and cost of energy," *Energy*, vol. 119, pp. 578–587, Jan. 2017, doi: 10.1016/j.energy.2016.11.021.

[79] "What is Monte Carlo Simulation?," Sep. 01, 2020. https://www.ibm.com/cloud/learn/monte-carlo-simulation (accessed Sep. 30, 2021).

[80] N. Growe-Kuska, H. Heitsch, and W. Romisch, "Scenario reduction and scenario tree construction for power management problems," in *2003 IEEE Bologna Power Tech Conference Proceedings,* Bologna, Italy, 2003, vol. 3, pp. 152–158. doi: 10.1109/PTC.2003.1304379.

[81] J. Almeida, B. Canizes, J. Soares, and Z. Vale, "Energy consumption and renewable generation data of 5 aggregators - 15 minute resolution (13 bus grid)." Zenodo, Dec. 29, 2020. doi: 10.5281/zenodo.4399670.

[82] B. Canizes, J. Soares, Z. Vale, and J. M. Corchado, "Optimal Distribution Grid Operation Using DLMP-Based Pricing for Electric Vehicle Charging Infrastructure in a Smart City," p. 40, 2019.

[83] J. Soares, B. Canizes, C. Lobo, Z. Vale, and H. Morais, "Electric Vehicle Scenario Simulator Tool for Smart Grid Operators," *Energies*, vol. 5, no. 6, pp. 1881–1899, Jun. 2012, doi: 10.3390/en5061881.

[84] "REGULATION (EU) 2018/ 858 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL - of 30 May 2018 - on the approval and market surveillance of motor vehicles and their trailers, and of systems, components and separate technical units intended for such vehicles, amending Regulations (EC) No 715/ 2007 and (EC) No 595/ 2009 and repealing Directive 2007/ 46/ EC," p. 218.

[85] J. Almeida, J. Soares, B. Canizes, F. Lezama, M. A. Ghazvini Fotouhi, and Z. Vale, "Evolutionary Algorithms for Energy Scheduling under uncertainty considering Multiple Aggregators," in *2021 IEEE Congress on Evolutionary Computation (CEC)*, Kraków, Poland, Jun. 2021, pp. 225–232. doi: 10.1109/CEC45853.2021.9504942.

[86] "Levelized Costs of New Generation Resources in the Annual Energy Outlook 2018," p. 25, 2018.

[87] "Levelized Cost of Energy (LCOE)," p. 9.